Analyzing Productivity Growth: Evidence from China's Manufacturing Industries

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Abstract

This article examines the growth attributes of manufacturing industries in China for the sample period of 1999-2007. All manufacturing industries are grouped into and four main industry groups and four geographical regions. A revised Solow's growth method is used to decompose the growth attributes into input growth, scale effect, technical progress, and technical efficiency change. A stochastic frontier model is applied to the translog production function. The empirical findings show a strong presence of technical progress, while labor input has rapidly been replaced by human capital. Structural transformation in the industrial sector is evident, so as regional imbalances.

Keywords: China industries, productivity, efficiency, technical progress, stochastic frontier model

JEL classification: L60, O14, O47, O53

I Introduction

China since the early 1950s had adopted socialist collectivization from the Soviet Union and pursued mainly heavy industries. Economic reform in 1978 came with a change of ideology under the late Deng Xiao-ping's motto that "it does not matter whether it is a black or white cat, so long as it catches mice". At the time of economic reform in 1978, there was a coexistence of excess supply in heavy industrial goods and excess demand in consumer goods (Perkins, 1988, 1994; Wu, 2005). The production of light manufacturing industries began to grow with the establishment of Special Economic Zones that provided investment advantages and low production cost along the coast of Southern China. Although industrial reform began in the mid-1980s, it was not until the mid-1990s when Shanghai was designated for development in high-technology industries (Wu, 2005). With a devaluation of 30 percent in the yuan in 1994, China's manufactured exports have since expanded continuously. According to the National Bureau of Statistics of China in 2006, manufacturing is the largest sector occupying 48.3 percent of real GDP, followed by service sector with 40.2 percent and primary sector has fallen to 11.5 percent.

Empirical studies on China's manufacturing sector have concentrated on a number of discussion areas. One area of discussion relates to the transformation to non-state-owned enterprises (Perkins, 1988). The 1997 state-owned enterprises reform has promoted the strategy of "grasping the large, releasing the small" (*juada fangxiao*) and expanded the number of non-state owned enterprises (Wu, 2005). In dealing with the data problem, the reported industrial output data have been adjusted by different benchmark years and benchmark industries in Ren and Zheng (2006), Wu (2002) and Maddison and Wu (2008). Szirmai *et al*. (2005) has pointed out that the construction of China's industrial data is needed more at the beginning stage of the reform era when data were missing, but data reliability has increased in recent years. Another area of discussion relates to the productivity and efficiency performance of industries, as studies have been conducted on individual industries, such as iron and steel, oil and aerospace, telecommunication and insurance (Jefferson, 1990; Movshuk, 2004; Ma *et al*., 2002; Mu and Lee, 2005; Yao *et al*., 2007). In studying productivity changes in China's industries, the Malmquist index that decomposes productivity into efficiency and technological changes has been applied in Ma *et al*. (2002) and Movshuk (2004), but Sun *et al*. (1999) and Yao *et al*. (2007) have argued that stochastic frontier and data envelopment analyses are more effective in measuring technical efficiency in China's industries.

Based on the data of 161 three-digit manufacturing industries in 31 provinces for the recent sample period of 1999-2007, this article studies the growth factors in China's manufacturing industries, and in particular, the issues of industrial productivity, technological progress and efficiency (Aigner *et al*., 1977; Kumbharkar and Lovell, 2000). In the empirical analysis, we apply the stochastic frontier model to the translog production function. This approach relaxes Solow's (1975) assumption of constant return to scale and optimal production capacity. The translog production function allows a flexible nonlinear functional form with non-constant returns to scale, while the stochastic frontier model provides the possibility of deviations between actual and optimal output due to technical inefficiency.

Section II shows the industrial data and the descriptive performance of industries in China. Section III discusses the methodology that decomposes TFP into three separate attributes, while Section IV reports the empirical results and the performance of different industries across provinces. The last section concludes the paper.

II Industrial Data and Performance

The online data *Support System for China Statistics Application* from the All China Marketing Research (ACMR) in Beijing provide a comprehensive industrial output and related information for a large number of four-digit manufacturing industries for the 31 provinces in China since 1999. The data for the 1999-2002 years show a total of 511 four-digit GB/T-94 coded manufacturing industries, but since 2003 the number has been reduced to 473 four-digit GB/T-2002 coded industries. These two sets of industry codes are compared, compiled and adjusted to eliminate classification and reporting inconsistencies. The standardized and adjusted four-digit manufacturing industries for the sample period of 1999-2007 are then aggregated into 161 three-digit and 29 two-digit industries, which are further grouped into four main industrial groups according to their digit category and level of technology (see Appendix Table A1). While the Processing Industry is based more on agriculture or raw materials, the Light Manufacturing Industry relates mainly to labor-intensive industries. The Metal and Machinery Industry contains the traditional heavy industries, while the High-technology Industry relates more to the modern technology-intensive industries. With a total of 161 industries in 31 provinces from 1999 to 2007, it gives about 29,812 data values after excluding missing observations (see Appendix Table A2).

The 31 provinces and autonomous areas in China are geographically grouped into four regions. The Eastern region includes the eleven provinces of Beijing, Tianjin, Hebei, Shanxi, Shanghai, Jiangsu, Zhejiang, Anhui, Shandong, Henan, and Hubei. Some provinces in the Eastern region are coastal provinces that experienced high initial economic growth and export expansion after the open door policy. The Southern region contains the eight provinces and autonomous areas of Fujian, Jiangxi, Hunan, Guangdong, Guangxi, Hainan, Chongqing, and Sichuan. Since economic reform in 1978, the Southern region adjacent to Hong Kong and Taiwan has been the recipient of foreign direct investment that concentrated in labor-intensive manufacturing. The Western region is remote and not easily accessible, and consists of a total of nine inner provinces and autonomous areas of Inner Mongolia, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. The Northeastern region adjacent to Japan and South Korea is the traditional heavy industry area that composes of the three provinces of Jilin, Heilongjiang and Liaoning.

Table 1 summarizes the data on the four groups of industries in four regions in the sample period. The total numbers of enterprises between 1999 and 2007 have doubled. The Metal and Machinery Industry is the largest industrial sector in terms of industrial sales output value and the number of enterprises and employees. The Processing Industry is the second largest industry in terms of the number of enterprises and employees, indicating that the Processing Industry is still based mainly on raw labor inputs. However, its industrial sales output value is the smallest among the four industrial groups. The Light Manufacturing Industry has expanded since economic reform in 1978, with the total numbers of enterprises and employees close to, but still lower than those in the Processing Industry. However, due to their high value-added content, the Light Manufacturing Industry has overtaken the Processing Industry for the industrial sales output value. The High-technology Industry has experienced the highest growth in the number of enterprises (288%) and employees (284%) between 1999 and 2007 among the four industrial groups, and its sales output value in 2007 has reached the level that lies between the Processing Industry and the Light Manufacturing Industry. Most importantly, the High-technology Industry has the highest percentage of industrial sales output value designated for export, about three to four times higher than the other three industrial groups. The export share in the Processing Industry output is the second largest, but its share has dropped considerably between the two sample years. Both the Light Manufacturing Industry and the Metal and Machinery Industry show the lowest export potential with mild changes only, suggesting that such outputs are geared mainly for the domestic market.

The regional performance in the sales output value and the numbers of enterprises and employees are similar among the four industrial groups. The Eastern region has the largest shares in sales output values and numbers of enterprises and employees. Each of these values in the Eastern region is much larger than the sum of the respective values in the other three regions. The Eastern region is thus the center of the manufacturing industrial production. Between the two sample years, sales output value and the numbers of industrial enterprises and employee have expanded most in the Eastern region, followed by the Southern region. The total number of industrial employees in the weaker Western and Northeastern regions has remained quite static. Among the four regions, the Southern region is strongest in terms of export delivery, followed by the Eastern region. Between 1999 and 2007, however, it is only the High-technology Industry that has significantly expanded in the percentage share of value of export, notably in the two richer Eastern and Southern regions. All other industries and regions show either a significant drop or a very mild increase in the performance of export between the two sample years.

Prior to the 1997 reform in state-owned enterprises (SOEs), a large number of conventional SOEs were loss-making, faced with huge inter-enterprises debts (the triangular debts) and relied heavily on state subsidy. The percentage of loss-making enterprises has declined by half in many cases between 1999 and 2007, especially in the two prosperous Eastern and Southern regions. The Eastern region has the lowest percentage of loss-making enterprises, while the weaker Western region still experiences a large (over 20%) percentage of loss-making enterprises.

The values of total industrial output deflated by the GDP deflator are used as the dependent variable in the production function. The independent variables include labor, physical capital and human capital. The total fixed assets deflated by the investment index are used as the proxy variable for physical capital. Since there is a lack of data on the educational level of industrial workers, a reliable proxy alternative would be the wage payments and related labor costs which are included in the operating expenses. Deflated by the GDP deflator, the operating expenses is thus used as the proxy for "human capital".[1]

[1] The missing 1999-2002 operating expenses data are estimated by interpolation from the 2003-2007 data.

Table 1 Performance of Industries in the Four Regions China: 1999 and 2007

Industry / Region	Total No. of Enterprises		Total No. of Employees (10,000)		Industrial Sales Output Value (Million 2,000 yuan)		% of Value of Export Delivery		% of Loss-making Enterprises	
	1999	2007	1999	2007	1999	2007	1999	2007	1999	2007
All Industries	139,080	303,513	4,241	6,669	5,743	27,131	18.49	21.13	27.30	13.49
Processing	39,919	77,844	1,188	1,804	1,475	4,998	24.27	18.41	29.80	13.41
Eastern	23,666	50,747	716	1,075	904	3,141	23.67	18.78	24.16	12.43
Southern	10,525	19,513	310	565	391	1,260	31.97	21.98	36.56	13.92
Western	3,113	2,946	82	76	103	268	5.83	4.10	42.92	22.74
Northeastern	2,615	4,638	80	88	77	329	16.88	12.77	38.01	16.00
Light Manufacturing	32,002	64,157	906	1,231	1,315	5,925	11.63	11.14	25.80	14.37
Eastern	18,692	38,172	528	677	808	3,657	10.40	11.05	20.00	12.21
Southern	8,361	18,367	219	379	293	1,288	19.11	15.53	32.78	14.93
Western	2,519	2,979	67	82	74	367	4.05	3.00	36.92	33.23
Northeastern	2,430	4,639	92	93	140	613	7.14	7.34	34.94	17.81
Metal & Machinery	53,310	121,607	1,706	2,380	1,933	10,750	12.11	12.64	26.58	12.57
Eastern	32,697	76,870	986	1,371	1,246	6,763	10.19	12.05	21.01	10.74
Southern	12,924	31,123	397	680	432	2,490	20.14	16.47	35.75	13.73
Western	3,778	4,332	135	135	97	464	4.12	5.39	38.27	30.84
Northeastern	3,911	9,282	188	194	158	1,033	10.13	10.55	31.58	15.34
High-technology	13,849	39,905	441	1,254	1,020	5,458	31.08	51.19	26.31	15.03
Eastern	8,360	24,237	225	600	559	3,176	22.54	47.29	22.85	12.54
Southern	4,201	13,462	167	598	400	2,053	43.50	60.30	30.45	18.60
Western	503	489	18	21	21	60	9.52	6.67	39.56	30.67
Northeastern	785	1,717	31	35	40	169	37.5	29.59	32.61	17.82

Source: *Support System for China Statistical Application*, All China Marketing Research, Beijing.

The Industrial Output Value at current prices in thousand yuan is the total value of industrial products, whether sold or ready for sales, in a certain period of time. It includes the value of all final products which are warehoused after inspection and packaging, or do not need any further processing. It also includes processing of foreign products, home-made semi-products, and changes in inventories. The Industrial Output Value is calculated with the "factory method", in that each individual industrial enterprise is regarded as a separate entity, and the final output of all the production activities is considered. This calculation method avoids double counting within the same enterprise.

In the construction of the physical capital in the study of industry productivity in China, investment figures have reliably been used as a proxy (Jefferson, 1989; Jefferson *et al*., 1992, 1996; Chen *et al*., 1988a, 1988b; Chow and Li, 2002; Li, 2003). The total fixed asset investment expressed in thousand yuan shows the enterprise's value of net fixed assets that includes liquidation of fixed assets, construction in progress, and loss of funds. The operating expenses expressed in thousand yuan refers to firms' expenses that include staff wages, travel, utilities, lease costs (excluding finance lease charges), repairs, staff welfare, staff education funds, union funds, labor protection, labor insurance, the board of directors fees, and management fees paid.[2]

III Stochastic Frontier Model and Decomposition of Output Growth

The growth attributes of industrial output is divided into input growth and TFP growth. In turn, the TFP growth is decomposed into adjusted scale effect, technical progress, and technical efficiency change (Kumbhakar and Lovell, 2000). The adjusted scale effect shows the returns to scale effect from combined inputs. Technical progress shows the rate of technological change and is indicated by an outward shift in the industry's production possibility frontier. Technical efficiency change refers to a movement from a position within to a position on the production frontier.

[2] Other items in the operations expenses are depreciation of fixed assets, business promotion expenses, business entertainment, electronic equipment running costs, security costs, property insurance companies costs, postal costs, foreign fees, printing costs, claims investigation costs, real estate tax, travel tax, land tax, stamp duty, meeting fees, legal fees, notary fees, consulting fees, amortization of intangible assets, amortization of long-term prepaid expenses, heating costs, audit fees, technology transfer fees, research and development fees, green fees and advertising.

The economic theory on efficient production argues that producers always produce at the maximized output level with given inputs. The empirical estimation on output, cost, and profit functions could produce variation in production efficiency (Farrell, 1957). The stochastic frontier production function without random shock can be stated as:

$$y_i = f(x_i)\exp(-u_i), \tag{1}$$

where y_i is the observed scalar output and x_i is a vector of inputs for i^{th} firm. The positive value of u_i is supposed to measure technical inefficiency. Technical efficiency can be written as:

$$TE_i = \frac{y_i}{f_i} = \exp(-u_i), \tag{2}$$

which is the ratio of observed output to maximum feasible output. It shows the output of the i^{th} firm relative to the stochastic frontier output that could be produced by a fully-efficient firm utilizing the same vector of inputs. Such an output-oriented measure of technical efficiency takes a value between zero and one. If $TE_i = 1$, then the firm is technically efficient.

By incorporating technical progress into the technical inefficiency specified in Equation (1), we represent the production function at time *t,* without the subscript *i* for firm, as:

$$y_t = f(x_{1t}, x_{2t}, \cdots, x_{kt}, t)e^{-u_t}, \tag{3}$$

where y_t is output and x_{jt} is the j input, $j = 1,2,\cdots,k$, at time *t*. Taking logarithm-differentiation of Equation (3) with respect to time, it gives:

$$\dot{y}_t = \sum_j \frac{\partial f}{\partial x_{jt}} \frac{x_{jt}}{f} \dot{x}_{jt} + \frac{\partial f}{\partial t}\frac{1}{f} - \frac{\partial u_t}{\partial t}, \tag{4}$$

where $\dot{y}_t = \frac{\partial y_t}{\partial t}\frac{1}{y_t}$ is the growth of output and $\dot{x}_{jt} = \frac{\partial x_{jt}}{\partial t}\frac{1}{x_{jt}}$ is the growth of input x_{jt}. The technical progress is $\dot{A}_t = \frac{\partial f}{\partial t}\frac{1}{f}$. Technical efficiency is $TE_t = \frac{y}{f} = e^{-u_t}$, while the growth of the technical efficiency is $\dot{TE}_t = -\frac{\partial u_t}{\partial t}$. Denote $e_{jt} = \frac{\partial f}{\partial x_{jt}}\frac{x_{jt}}{f}$ as the output elasticity with respect to input x_{jt}. The output growth can be represented as:

$$\dot{y}_t = \sum_j e_{jt}\dot{x}_{jt} + \dot{A}_t + T\dot{E}_t . \tag{5}$$

The first term in the above decomposition can further be decomposed into two different terms using the cost minimization condition. Consider the cost minimization problem of the objective function: $\min_{x_{jt}} C_t$, where $C_t = \sum_j w_{jt}x_{jt}$, subject to the constraint in Equation (3). In the Lagrangian form, the objective function and the constraint are written as:

$$L(x_{jt},\lambda) = \sum_j w_{jt}x_{jt} + \lambda(y_t - fe^{-u_t}), \tag{6}$$

where λ is the Lagrange multiplier. The first-order condition for minimization is:

$$w_{jt} = \lambda \frac{\partial f}{\partial x_{jt}} e^{-u_t} . \tag{7}$$

Multiplying both sides by x_{jt},

$$w_{jt}x_{jt} = \lambda \frac{\partial f}{\partial x_{jt}} x_{jt}e^{-u_t} = \lambda \frac{\partial f}{\partial x_{jt}} \frac{x_{jt}}{f} fe^{-u_t} = \lambda e_{jt} y_t . \tag{8}$$

Taking the sum for all input, the total cost C_t is:

$$C_t = \sum_j w_{jt}x_{jt} = \sum_j \lambda e_{jt} y_t = \lambda e_t y_t , \tag{9}$$

where $e_t = \sum_j e_{jt}$ is the sum of output elasticities to input. It can be shown that e_t is a measure of returns to scale. Suppose changes in all inputs have the same scale, $\Delta x_{jt} = ax_{jt}$. Consider the changes in output Δf by taking the total derivative of $f(x_1, x_2, \cdots, x_n, t)$ and substituting $\Delta x_{jt} = ax_{jt}$ into Δf, we have:

$$\Delta f = \sum_j \frac{\partial f}{\partial x_{jt}} \Delta x_{jt} + \frac{\partial f}{\partial t}\Delta t = f\sum_j \frac{\partial f}{\partial x_{jt}} \frac{ax_{jt}}{f} + f\dot{A}_t = fa\sum_j e_{jt} + f\dot{A}_t = afe_t + f\dot{A}_t . \tag{10}$$

Without considering technical progress, the production function shows increasing (constant, decreasing) returns to scale when $e_t > 1$ (= 1, < 1). Dividing Equation (8) by Equation (9), the cost share for input j is:

$$s_{jt} = \frac{w_{jt}x_{jt}}{C_t} = \frac{e_{jt}}{e_t}. \tag{11}$$

This shows that the cost share is always equal to the relative output elasticity in the case of cost minimization. For the constant returns to scale, $e_t = 1$, the cost share is equal to output elasticity. Inserting $e_t \dfrac{1}{e_t}$ into Equation (5) and rearrange terms, we can rewrite the output growth as:

$$\dot{y}_t = \sum_j \frac{e_{jt}}{e_t}\dot{x}_{jt} + (e_t - 1)\sum_j \frac{e_{jt}}{e_t}\dot{x}_{jt} + \dot{A}_t + T\dot{E}_t. \tag{12}$$

Using the cost share Equation (11),

$$\dot{y}_t = \sum_j s_{jt}\dot{x}_{jt} + (e_t - 1)\sum_j s_{jt}\dot{x}_{jt} + \dot{A}_t + T\dot{E}_t. \tag{13}$$

In the above, output growth is decomposed into four sources: input growth $\dot{\Phi}_t = \sum_j s_{jt}\dot{x}_{jt}$, adjusted scale effect $(e_t - 1)\dot{\Phi}_t$, technical progress $\dot{A}_t$, and the growth of technical efficiency $T\dot{E}_t$. The first term represents the contribution of input growth to the output growth. The growth of aggregate input ($\dot{\Phi}$) is the weighted sum of all input growth. The weight is the cost share of the input, which is also the ratio of output elasticity of an input. The second term is the adjusted scale effect. The contribution of increasing returns to scale to output growth is positive $(e-1) > 0$, and the scale effect of ($e-1$) is adjusted by the growth of aggregate input ($\dot{\Phi}$). For constant returns to scale ($e=1$) or zero input growth ($\dot{\Phi} = 0$), the adjusted scale effect is zero. The third term $\dot{A}_t$ is a measure of technical progress and the last term $T\dot{E}_t$ refers to the change in technical efficiency. This decomposition is different from Solow's growth decomposition (Solow, 1957) in two ways. First, this decomposition allows non-constant returns to scale. Second, it considers the change in technical efficiency.

With the decomposition of output growth as shown by Equation (13), we can easily derive the decomposition of the growth of TFP. Define the TFP for a production function with multiple inputs at time t as:

$$TFP_t = \frac{y_t}{\Phi_t}, \tag{14}$$

where Φ is the aggregate input. Assuming $\dot{\Phi}_t = \sum_j s_{jt}\dot{x}_{jt}$, the growth of TFP is:

$$T\dot{F}P_t = (e_t - 1)\sum_j s_{jt}\dot{x}_{jt} + \Delta\delta_t + T\dot{E}_t. \tag{15}$$

The decomposition of output and productivity growth shown in Equations (13) and (15) will empirically be applied to the data. The stochastic frontier model assumes deviations from the efficient frontier with random shock (Aigner *et al*., 1977). The specification of technical inefficiency in Equation (1) might also capture other random shocks that are either beyond the control of the firm or not directly attributable to the underlying technology. The random shocks can be included in the translog production frontier function by adding a two-sided error term (Greene, 1980).[3] The stochastic frontier model with panel data then becomes:

$$\begin{aligned}\ln Y_{it} = \beta_0 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_H \ln H_{it} + \beta_{KK}(\ln K_{it})^2 + \beta_{LL}(\ln L_{it})^2 + \beta_{HH}(\ln H_{it})^2 \\ + \beta_{KL}\ln K_{it}\ln L_{it} + \beta_{KH}\ln K_{it}\ln H_{it} + \beta_{LH}\ln L_{it}\ln H_{it} + \sum_t \delta_t D_t + v_{it} - u_{it},\end{aligned} \tag{16}$$

where i=1, …N industries and t=1, …T; $\ln Y_{it}$ is the log of real industrial output for i^{th} industry at time t. $\ln K_{it}$ is the log of total fixed asset investment used as a proxy for physical capital, $\ln L_{it}$ is the log of total number of employed workers, $\ln H_{it}$ is the log of operating expenses used as a proxy for the human capital variable. D_t is the time dummy variable that captures technical progress and the parameter δ_t can be used to measure technical progress over time. The random error v_{it} is symmetric and normally distributed with $v_{it} \sim N(0, \sigma_v^2)$. The technical inefficiency term u_{it} can either be time invariant or time variant (Kumbhakar and Lovell, 2000). In the case of time invariant technical inefficiency, $u_{it} = u_i \sim N^+(\mu, \sigma_u^2)$, where μ is the mode of the

[3] We follow the classical growth model with exogenous inputs. If the endogeneity of inputs occur, the estimated coefficients will be biased and the conclusion from this paper may be conservative. Liu and Li (2006) controls endogeneity of human capital by applying the two lags of human capital as instruments. However, their estimation of the production function does not include technical inefficiency.

truncated half-normal distribution. In the case of time variant technical inefficiency, u_{it} can be expressed as a monotonic 'decay' function as $u_{it} = \eta_t u_i$, where $\eta_t = \exp(-\eta(t-T))$, and η is an unknown scalar parameter for technical inefficiency. u_{it} can either be increasing (if $\eta < 0$), decreasing (if $\eta > 0$) or remained constant (if $\eta = 0$) (Battese and Coelli, 1992). The minimum-mean-square-error predictor of the technical efficiency of the i^{th} industry at time t is shown as (Battese and Coelli, 1988, 1992, 1995; Battese and Corra, 1977; Coelli, 1996; Kumbhakar and Lovell, 2000):

$$TE_{it} = E(\exp(-u_{it}) | \varepsilon_{it}), \tag{17}$$

where $\varepsilon_{it} = v_{it} - u_{it}$.

Ignoring the random shock term, the decomposition of output growth, $\dot{Y}_{it}$, and total factor productivity growth, $T\dot{F}P_{it}$, can be derived from Equations (13) and (15) as:

$$\dot{Y}_{it} = \dot{\Phi}_{it} + Scale_{it} + \Delta\delta_{it} + T\dot{E}_{it}, \tag{18}$$

$$T\dot{F}P_{it} = Scale_{it} + \Delta\delta_{it} + T\dot{E}_{it}, \tag{19}$$

$$\dot{\Phi}_{it} = \frac{e_{K_{it}}}{e_{it}}\dot{K}_{it} + \frac{e_{L_{it}}}{e_{it}}\dot{L}_{it} + \frac{e_{H_{it}}}{e_{it}}\dot{H}_{it}, \tag{20}$$

$$Scale_{it} = (e_{it} - 1)\left(\frac{e_{K_{it}}}{e_{it}}\dot{K}_{it} + \frac{e_{L_{it}}}{e_{it}}\dot{L}_{it} + \frac{e_{H_{it}}}{e_{it}}\dot{H}_{it}\right), \tag{21}$$

where $\dot{K}$, $\dot{L}$, and $\dot{H}$ are growth of inputs; e is returns to scale. e_K, e_L, and e_H are output elasticities for physical capital, labor, and human capital, respectively:

$$e_{K_{it}} = \beta_K + 2\beta_{KK}\ln K_{it} + \beta_{KL}\ln L_{it} + \beta_{KH}\ln H_{it}, \tag{22}$$

$$e_{L_{it}} = \beta_L + 2\beta_{LL}\ln L_{it} + \beta_{KL}\ln K_{it} + \beta_{LH}\ln H_{it}, \tag{23}$$

$$e_{H_{it}} = \beta_H + 2\beta_{HH}\ln H_{it} + \beta_{KH}\ln K_{it} + \beta_{LH}\ln L_{it}. \tag{24}$$

To derive the estimates for the components in the growth and productivity decomposition, we first use the maximum likelihood method to estimate the parameters in Equation (16). Substituting the estimated coefficients of $\beta's$ in Equation (16) into the above three equations gives $\hat{e}_{K_{it}}$, $\hat{e}_{L_{it}}$, and $\hat{e}_{H_{it}}$. The estimates of output elasticities and individual input growth can be used to estimate the first two components of output growth: growth of aggregate input and adjusted scale effects. Given the estimated coefficient of δ_t in Equation (16), the estimate of technical progress is $\Delta\hat{\delta} = \frac{1}{T-1}\sum_t (\hat{\delta}_t - \hat{\delta}_{t-1})$. In the case of the time-varying decay technical efficiency $u_{it} = \exp(-\eta(t-T))u_i$, the change in technical efficiency can be estimated by:

$$\hat{\dot{TE}} = \frac{1}{NT}\sum_{i,t} \hat{\eta}\exp(-\hat{\eta}(t-T))\,\hat{u}_{ii}, \qquad (25)$$

where $\hat{u}_{it}$ is the estimate of technical efficiency and $\hat{\eta}$ is the estimate of time-varying decay parameter. For the time invariant technical efficiency, we have $\eta_t = 0$ and $\dot{TE}_t = 0$ for all *t*.

IV Empirical Results

The stochastic frontier production shown in Equation (16) contains a total of eight time dummy variables with 1999 as the benchmark year that serve to capture technical progress over time. When the regression includes the industrial data from all provinces, we include three regional dummy variables of Southern, Western, and Northeastern regions, while the Eastern region is regarded as the benchmark (Szirmai *et al*., 2005).

In estimating technical efficiency, we consider two types of stochastic frontier models with time-invariant technical inefficiency, $u_{it} = u_i$ for all *t*, and time-varying decay technical inefficiency, $u_{it} = \exp(-\eta(t-T))u_i$. For the time-invariant technical inefficiency model, the estimate of the change of technical efficiency is zero, namely $\dot{TE} = 0$. For the time-varying decay technical inefficiency model, a positive estimate of the time-varying decay parameter μ gives positive $\dot{TE}$ and implies an improvement of technical inefficiency. When we apply the time-varying decay technical inefficiency model to different data sets, the result shows that there are several cases with negative growth in technical efficiency ($\dot{TE} < 0$) for a given data set. We find that a negative growth in technical inefficiency is always accompanied by an unusual large technical progress. However, the sum of estimates of the technical progress and the growth in technical efficiency ($\Delta\delta_t + \dot{TE}$) is close to the estimate of technical progress for the time-invariant technical inefficiency model. We consider this is an identification problem in the estimation and use the results from the time-invariant technical inefficiency model.

Estimates for the Aggregate and the Four Industrial Groups

Table 2 presents the estimates of Equation (16) for the aggregates of all industries and the four groups of manufacturing industries. Columns (1) and (2) in Table 2 show, respectively, the estimates for the time-decay variant and time-invariant technical inefficiency models for the aggregates of all industries. We remove the Southern region in column (1) since it is not significant in the estimation. The estimates of μ show that the mode for the truncated half-normal distribution of the technical inefficiency term u_{it} is significantly greater than zero for column (1), but not significant in column (2). The technical inefficiency term in Column (2) appears to have half-normal distribution, instead of truncated half-normal distribution. In spite of the difference in the assumption of time-variant and time-invariant technical inefficiency, most estimated coefficients from these two models are very close. Since the estimate for the time-varying decay parameter η shown in column (1) is not significant, the time-invariant technical inefficiency model shown in column (2) is more appropriate than the time-varying decay technical inefficiency model shown in column (1).

For the four industrial groups, we only find that the High-technology Industry has the time-varying decay technical inefficiency property, as shown in column (6). The estimated coefficient of the time-varying decay parameter (η) for the High-technology Industry is 0.034, which indicates an improvement in technical efficiency. The rest of the three columns for the other three industrial groups contain the estimates from the time-invariant of technical inefficiency model.

Table 2 shows that almost all estimated coefficients of the inputs (physical capital, labor, and human capital) are significant at 5 percent level. We apply χ^2 test for the significance of the six nonlinear terms. The statistics $\chi^2(nonlinear)$ are all significant and show that the translog function is more appropriate than the Cobb-Douglas function for the aggregates and all four industrial groups. Because of the nonlinear relationship in the translog function, the relationship between inputs and output should best be described by the output elasticities (shown in Table 3).

Table 2 Regression Estimates of the Industry Aggregates and Four Industrial Groups

	All Industries (1)	All Industries (2)	Processing Industry (3)	Light Manufacturing (4)	Metal and Machinery (5)	High-technology (6)
ln K	-0.143	-0.138	-0.588	-0.222	0.032	0.148
	(0.026)	(0.025)	(0.073)	(0.037)	(0.045)	(0.083)
ln L	0.994	1.017	1.411	1.112	0.933	0.534
	(0.030)	(0.029)	(0.073)	(0.047)	(0.054)	(0.090)
ln H	0.631	0.707	0.696	0.427	0.729	0.999
	(0.036)	(0.035)	(0.077)	(0.064)	(0.055)	(0.116)
ln K × ln K	0.014	0.014	0.039	0.017	0.011	-0.029
	(0.003)	(0.003)	(0.007)	(0.004)	(0.005)	(0.010)
ln L × ln L	-0.022	-0.021	-0.026	-0.014	-0.011	-0.059
	(0.004)	(0.004)	(0.009)	(0.007)	(0.007)	(0.013)
ln H × ln H	-0.052	-0.055	-0.092	-0.085	-0.053	-0.043
	(0.006)	(0.006)	(0.013)	(0.011)	(0.009)	(0.016)
ln K × ln L	0.006	0.004	-0.017	-0.007	-0.004	0.101
	(0.006)	(0.006)	(0.015)	(0.010)	(0.011)	(0.022)
ln K × ln H	0.037	0.033	0.057	0.080	0.031	0.019
	(0.007)	(0.007)	(0.015)	(0.012)	(0.012)	(0.020)
ln L × ln H	-0.043	-0.043	-0.070	-0.074	-0.040	-0.056
	(0.008)	(0.008)	(0.016)	(0.014)	(0.013)	(0.022)
South		-0.155	-0.129	-0.109	-0.201	-0.171
		(0.021)	(0.051)	(0.036)	(0.031)	(0.057)
Northeast	-0.169	-0.236	-0.165	-0.192	-0.292	-0.203
	(0.028)	(0.029)	(0.072)	(0.051)	(0.043)	(0.080)
West	-0.432	-0.544	-0.514	-0.570	-0.573	-0.474
	(0.022)	(0.023)	(0.055)	(0.041)	(0.033)	(0.069)
Constant	6.473	7.171	6.711	7.724	5.107	5.942
	(0.451)	(44.028)	(0.354)	(38.965)	(1.179)	(0.392)
μ	2.443	3.334	1.698	3.249	2.049	1.842
	(0.443)	(44.027)	(0.204)	(38.964)	(1.166)	(0.177)
η	0.002					0.034
	(0.002)					(0.005)
$\chi^2(nonlinear)$	369.20	382.26	203.19	263.01	70.69	59.59
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\chi^2(regions)$	382.72	576.50	88.94	198.80	298.26	48.00
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\chi^2(time)$	336.28	5612.82	948.67	1400.91	3088.17	15.18
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.056)
Nobs	28,915	28,915	6,233	8,028	11,692	3,859

Note: The figures in the parenthesis under the estimates are standard errors. The figures in the parenthesis under the chi-squares statistics are p-values. Nobs = number of observations. The data from Guizhou and Tibet are removed from the estimation for columns (1) and (2).

Table 2 shows that the estimated coefficients of regional dummies are all negative and significant. The χ^2 tests for the joint hypothesis test of all regional dummy variables, χ^2 (*regions*), are all significant as well. This implies that output growth in the Southern, Northeastern, and Western regions is smaller than output growth in the Eastern region. The coefficient for the Western region is the smallest, suggesting that the Western region has the slowest growth rate, as its growth is about 0.5 percent lower than the Eastern region. The results of these dummy variables provide an evidence of imbalanced growth among the four regions.

The estimated coefficients for the time dummy variables are not shown in Table 2, but the joint hypothesis tests for the coefficients of time dummy variables χ^2 (*time*) are displayed. All the test statistics are significant at 5 percent level for the aggregates and industrial groups, except for the High-technology Industry. The p-value of the χ^2 (*time*) test for the High-technology Industry is 5.6 percent, suggesting that the technical progress estimates may not be significant for the High-technology Industry.

Equations (18) and (19) show the decomposition of output growth ($\dot{Y}$) and total factor productivity growth ($T\dot{F}P$). To estimate the components of output and productivity growth, we use Equations (21) – (25) to derive the estimates for the output elasticity with respect to the three inputs of capital, labor and human capital (e_K, e_L and e_H, respectively), returns to scale (e), input growth ($\dot{\Phi}_t$), adjusted scale effect ($Scale$), rate of technical progress ($\Delta\delta_t$), and growth of technical inefficiency ($T\dot{E}$). Table 3 shows these estimates for the industry aggregates and the four industrial groups. Note that the estimates for the industry aggregates and the three industrial groups are based on the model with time invariant technical efficiency and $T\dot{E} = 0$; only the estimates for the High-technology Industry are from the model with time-varying decay technical efficiency.

Table 3 produces a number of observations. Labor has the largest output elasticity among the three inputs. For the aggregates of all industries, the output elasticities for labor, human capital, and physical capital are 0.617, 0.501 and 0.335, respectively. The estimates of these three elasticities in four industrial groups are similar to those for the aggregates; the output elasticities for labor (between 0.601 and 0.658) are the largest, followed by the output elasticities for human capital (between 0.427 and 0.558) and the output elasticities for physical capital (between 0.311 and 0.372).

The largest cost share is Labor. For the aggregates of all industries, labor's cost share is 42.5 percent; human and physical capital's shares are 34.5 percent and 23.1 percent, respectively. For the four industrial groups, the cost shares for the three inputs are similar to those in the aggregates. The Light Manufacturing Industry has the largest labor cost share (44.6%). The High-technology Industry has the largest cost share in human capital (36.5%). The Processing Industry has the largest cost share in physical capital (26.5%). These cost shares are in line with expectations given the labor-intensive and capital-intensive nature of different industrial groups.

Table 3 Growth Decomposition for the Aggregates and Four Industrial Groups

	Output Elasticity				Cost Share		
	e_K	e_L	e_H	e	s_K	s_L	s_H
Aggregates	0.335	0.617	0.501	1.453	0.231	0.425	0.345
Processing	0.372	0.605	0.427	1.404	0.265	0.431	0.304
Light Manufacturing	0.322	0.618	0.446	1.386	0.232	0.446	0.322
Metal and Machinery	0.337	0.601	0.538	1.477	0.228	0.407	0.364
High-technology	0.311	0.658	0.558	1.527	0.204	0.431	0.366

	Input Growth Effect (%)				Scale Effect (%)	
	$s_K\dot{K}$	$s_L\dot{L}$	$s_H\dot{H}$	$\dot{\Phi}$	$e-1$	$(e-1)\dot{\Phi}$
Aggregates	2.00	1.50	3.39	6.89	0.45	3.08
Processing	1.34	0.85	2.98	5.17	0.39	2.04
Light Manufacturing	2.35	1.71	3.01	7.07	0.38	2.71
Metal and Machinery	2.07	1.38	3.67	7.12	0.47	3.35
High-technology	2.08	2.56	3.73	8.37	0.52	4.35

	Estimated $\dot{Y}$	$\dot{\Phi}$	Scale	$\Delta\delta_t$	$T\dot{E}$	$T\dot{F}P$	$\dot{Y}$	
	(1)	(2)	(3)	(4)	(5)	(3)+(4)+(5)	(7)	(7)-(1)
Aggregates	18.06	6.89	3.08	8.10	0	11.18	18.19	0.13
Processing	14.63	5.17	2.04	7.43	0	9.46	14.51	-0.13
Light Manufacturing	16.95	7.07	2.71	7.17	0	9.88	17.54	0.60
Metal and Machinery	19.83	7.12	3.35	9.36	0	12.71	19.92	0.10
High-technology	20.56	8.37	4.35	0.92	6.92	12.19	20.26	-0.30

Note: Estimated $\dot{Y}$ or estimated growth of output is the sum of input growth ($\dot{\Phi}$) and $T\dot{F}P$. $T\dot{F}P$ is the sum of adjusted scale effect (*Scale*), technical progress ($\Delta\delta_t$) and change in technical efficiency ($T\dot{E}$). $\dot{Y}$ is the actual output growth and the last column shows the estimation errors.

Human capital grows faster than the other two inputs. The input growth for the aggregates of all industries amounted to 6.89 percent, but human capital has the fastest growth with 3.39 percent, while the growth for physical capital and labor are 2.0 percent and 1.5 percent, respectively. All four industrial groups have similar patterns of input growth.

There are signs of structure change in the manufacturing industries. The input growth has shifted from the Processing Industry to the other industrial groups. The High-technology Industry has the highest input growth, followed by the Metal and Machinery industry, the Light Manufacturing Industry, and the Processing Industry, with 8.37 percent, 7.2 percent, 7.07 percent, 5.17 percent, respectively. The high input growth in both High-technology Industry and Metal and Machinery Industry is due mainly to the growth in human capital. The low input growth for Processing Industry is because of low labor growth.

Industrial production exhibits increasing returns to scale. The sum of three output elasticities for the aggregates of all industries and each of four industrial groups is greater than one. The returns to scale for the aggregates are 1.453; the returns of scale for four industrial groups have a range from the Light Manufacturing Industry (1.386) to the High-technology Industry (1.527). Industrial production shows positive adjusted scale effects, due probably to the positive input growth and increasing returns to scale. The adjusted scale effect is 3.08 percent for the aggregates of all industries. Among the four groups of industries, the High-technology Industry has the highest adjusted scale effects (4.35%). The input growth for Light Manufacturing Industry and Metal and Machinery Industry are similar, the adjusted scale effect for the Metal and Machinery Industry is higher since it has a higher returns to scale. The Processing Industry has the lowest adjusted scale effect, caused mainly by the low input growth.

Only the High-technology Industry shows a positive improvement of technical efficiency. Based on the test statistics of the time-varying decay parameter (not shown in the table), the aggregates of all industries and the rest three industrial groups have no changes in technical efficiency, namely $T\dot{E} = 0$. For the High-technology Industry, the improvement of technical efficiency is 6.92 percent and the technical progress is only 0.92 percent.

Technical progress is more important than input growth and adjusted scale effects for the aggregates of all industries and three industrial groups (Processing, Light Manufacturing and Metal and Machinery). For the aggregates of all industries, the contribution of technical progress, input growth, and adjusted scale effects to the output growth are 45 percent, 38 percent, and 17 percent (8.1%, 6.89%, and 3.08% out of 18.06%), respectively. The TFP, which is the sum of the adjusted scale effects and technical progress, contributes about 62 percent to total output growth.

Another sign of structure change in the manufacturing industries is the high TFP growth in the Metal and Machinery Industry and the High-technology Industry. The TFP growths for these two industrial groups are higher than those for the Processing and Light Manufacturing industrial groups (12.71% and 12.19% vs. 9.46% and 9.88%, respectively). The high TFP growth, together with high input growth, leads to higher output growths for the Metal and Machinery Industry and the High-technology Industry than the other two industrial groups (19.83% and 20.56% vs. 14.63% and 16.95%, respectively). The Metal and Machinery Industry has the highest rate of technological progress (9.36%) and the highest growth rate of TFP (12.71%), reflecting the continued importance of the conventional heavy industry. The high output growth for the High-technology Industry can be explained by high input growth (8.37%) and adjusted scale effects (4.35%), which are the highest in four industrial groups. The fast growth of the emerging High-technology Industry is the key structure transformation in China's industrial production. Lastly, the estimated decomposition generated relatively small statistical error. The absolute values of the errors between the estimated output growth and the actual output growth are all less than 1 percent.

Estimates for the 29 Two-digit Industries

The 161 three-digit industries are aggregated into 29 two-digit industries (Appendix Table A1). For example, the Processing Industry contains 53 three-digit industries between the codes 131 and 195. Among these industries, the industries between 131 and 139 are aggregated into one industry with the code of "13"; the industries between 140 and 149 are aggregated into the industry with the code of "14", and so on. The two-digit industries with a code from 13 to 19, 20 to 29, 30 to 37 and 40 to 43 belong to Processing Industry, Light Manufacturing Industry, Metal and Machinery Industry and High-technology Industry, respectively. The estimates of growth decomposition for each of these 29 two-digit industries shown in Table 4 provide a detailed view of the manufacturing industries.

Table 4 Growth Decomposition for Two-digit Industries (%)

	Industry (code)	Estimated $\dot{Y}$	$\dot{\Phi}$	Scale	$\Delta\delta_t$	$T\dot{E}$	$T\dot{F}P$	$\dot{Y}$	
		(1)	(2)	(3)	(4)	(5)	(3)+(4)+(5)	(7)	(7)-(1)
Processing	13	15.87	5.97	2.30	7.61	0	9.90	15.83	-0.04
	14	18.44	6.83	3.33	8.27	0	11.61	17.55	-0.89
	15	16.52	7.12	1.87	1.88	5.66	9.40	16.57	0.05
	16*	3.83	3.72	3.76	-3.65	0	0.11	5.48	1.66
	17	11.60	1.65	0.68	9.28	0	9.96	11.09	-0.51
	18	11.27	5.29	2.22	3.76	0	5.98	11.53	0.26
	19	15.06	4.74	0.58	9.74	0	10.32	15.01	-0.05
Light Manufacturing	20	19.58	8.33	2.94	8.31	0	11.25	19.97	0.39
	21	18.59	10.51	5.06	3.02	0	8.08	19.03	0.43
	22	12.15	3.64	1.82	6.69	0	8.51	12.66	0.51
	23	8.95	4.06	2.24	2.65	0	4.89	10.58	1.63
	24	20.50	11.94	4.78	3.78	0	8.56	21.30	0.80
	25*	27.69	9.42	2.13	16.13	0	18.26	28.13	0.44
	26	18.23	6.73	1.43	10.06	0	11.50	19.01	0.78
	27	15.62	7.25	3.47	4.90	0	8.37	15.75	0.13
	28	14.83	5.04	2.44	7.34	0	9.79	13.57	-1.25
	29	14.33	4.89	1.66	7.77	0	9.43	14.88	0.55
Metal and Machinery	30	16.30	6.68	2.02	7.60	0	9.62	16.99	0.68
	31	16.58	4.93	2.29	9.36	0	11.65	16.67	0.09
	32	22.31	5.87	2.21	14.23	0	16.44	22.18	-0.13
	33*	30.95	11.22	4.39	15.34	0	19.73	31.57	0.63
	34	19.41	8.25	2.62	6.68	1.86	11.16	18.91	-0.51
	35	20.03	5.95	3.95	10.14	0	14.08	20.32	0.29
	36	19.62	6.10	4.60	8.92	0	13.52	19.48	-0.14
	37	22.47	9.58	4.88	8.01	0	12.89	22.26	-0.21
High-tech	40	21.57	8.07	4.13	5.27	4.10	13.50	21.34	-0.23
	41	18.11	8.34	4.70	0.31	4.76	9.77	16.35	-1.76
	42	20.76	8.37	4.52	2.57	5.30	12.39	22.02	1.25
	43	24.12	9.79	2.13	12.19	0	14.32	24.56	0.44
	Average*	17.42	6.77	2.88	7.77	–	10.65	17.52	0.10
	Std	3.78	2.29	1.33	2.71	–	2.60	3.76	0.72
	Minimum	8.95	1.65	0.58	2.65	–	4.89	10.58	-1.76
	Maximum	24.12	11.94	5.06	14.23	–	16.44	24.56	1.63

Note: * Industrial codes 16, 25, and 33 are removed from the descriptive statistics calculation shown in the last four rows.

Due probably to deliberate policy on health hazards, the tobacco processing industry (code #16) has an unusual low growth of 3.83 percent. The two unusual high output growth industries are the oil industry (code #25) and the metal smelting and alloys industry (code #33), with growth rates of 27.69 percent and 30.95 percent, respectively. The high output growth for these two industries is due to technical progress and the high demand for energy and metal products. If we remove these three industries as outliers, the growth from the remaining 26 two-digit industries still has a large variation, ranging from 8.95 percent to 24.12 percent.

The high variation of output growth for the two-digit industries is accompanied by high variation in input growth, scale effect, and the combined effect of the technical progress and the change in technical efficiency. The input growth for two-digit industrials has an average of 6.77 percent and ranges from 1.65 percent to 11.94 percent (excluding industry codes #16, #25, and #33). Except the four two-digit industries in High-technology Industry, the two-digit industries in the rest three main industrial groups have large variation of input growth. The adjusted scale effect shows an average of 2.88 percent and a range from 0.58 percent to 5.06 percent. This effect has a higher variation for the two-digit industries in the Processing Industry and the Light Manufacturing Industry than the Metal and Machinery Industry and the High-technology Industry, all of which have an adjusted scale effect of higher than 2 percent. The combined effect of the technological progress and the change in the technical efficiency shows an average of 7.77 percent, higher than the input growth, but the range from 2.65 percent to 14.23 percent is larger than the range for input growth. For the performance of TFP growth, the average is 10.65 percent with a range between 4.89 percent and 14.23 percent. These large percentage ranges reflect the diverse performance of the individual industries in the sample period. All but three two-digit industries enjoyed a growth rate of TFP in excess of 8 percent, with two close to 20 percent.

The structure change in the manufacturing industrials can also be found in the two-digit industries estimates. The input growth for all two-digit industries in the Processing Industry are lower than 8 percent while the input growth for all four two-digit industries in the High-technology Industry are more than 8 percent. Most two-digit industries in the Metal and Machinery Industry and the High-technology Industry have the growth of TFP more than 10 percent and most industries in the rest of the two main industries have the growth rate of TFP less than 10 percent.

With the exception of five industries (codes # 15, 34, 40, 41 and 42), there is an absence of technical efficiency change in the majority of industries. Three of the five industries with technical efficiency change are in the High-technology Industry. The estimation of growth decomposition in two-digit industries also has a small statistical error. There are five industries that have an absolute estimation error greater than 1 percent and all other 24 industries have an error less than 1 percent between the actual output growth and estimated output growth.

Our empirical results for the manufacturing industries in Tables 3 and 4 shows that the industrial output growth can be explained by input growth, adjusted scale effect, technical progress, and the change in technical efficiency. For the aggregates of all industries, input growth explains 38 percent, adjusted scale effect explains 17 percent, and technical progress explains 45 percent of output growth, but there is no evidence of technical efficiency change. Contrary to the findings in Young (2000, 2003) and Li (2009) that China's post-reform GDP growth has depended largely on capital inputs, our results using more recent industrial data show that technical progress is more important than input growth for manufacturing industries. Furthermore, increasing returns to scale plays an important role for the industrial output growth. Traditionally, the contribution from the scale effect has been ignored. With the inclusion of the scale effect in the analysis of growth in TFP, we found that the scale effect explains about 27 percent of the growth of TFP (17% out of 62%). Among the three inputs in the production function, our results show that human capital contributes about one-half of total input growth and the contribution from physical capital has surpassed the contribution from labor. Despite the large labor force, recent studies (Fleisher *et al*., 2010; Li *et al*., 2009) showed that human capital has been lacking, especially in the middle-management range. Our results indicate that manufacturing industries do attract the formation and growth of human capital.

The empirical results also show structure change from light industries to heavy and technology-intensive industries. In general, the industries in the Metal and Machinery Industry and the High-technology Industry have a higher output growth than the other two industry groups due to high input growth and high TFP growth. The high input growth for the Metal and Machinery Industry / High-technology Industry is related to the growth of human capital / labor and human capital. This suggests that the labor movement from light industries to heavy and technology-intensive industries is also accompanied by growth in human capital, especially in the High-technology Industry. Certain two-digit heavy industries in the Metal and Machinery

Industry have low labor growth because these industries require more physical capital and human capital than labor. Most two-digit industries in the High-technology Industry contain newly formed business and industries, which induces the high demand for the labor force and high labor growth. For all four main industrial groups and 29 two-digit industries, we only find the improvement of technical efficiency in the High-technical Industry and five two-digit industries, three of them are in the High-technical Industry.

Table 5 Growth Decomposition for Four Industrial Groups in Four Regions

	Estimated $\dot{Y}$	$\dot{\Phi}$	Scale	$\Delta\delta_t$	$T\dot{E}$	$T\dot{F}P$	$\dot{Y}$	
	(1)	(2)	(3)	(4)	(5)	(3)+(4)+(5)	(7)	(7)-(1)
				Eastern Region				
All	16.74	6.52	2.82	7.41	0	10.23	16.81	0.07
Processing	11.88	4.45	1.70	5.72	0	7.42	12.08	0.21
Light Manuf.	14.99	5.95	2.36	6.69	0	9.04	15.50	0.51
Metal & Machi.	18.85	7.17	2.97	8.71	0	11.68	18.87	0.03
High-tech	21.22	8.57	4.77	1.76	6.12	12.65	20.31	-0.91
				Southern Region				
All	20.58	8.82	4.41	3.20	4.15	11.76	21.13	0.54
Processing	17.11	7.32	4.00	5.80	0	9.80	17.37	0.26
Light Manuf.	19.75	9.41	4.07	2.54	3.74	10.35	20.57	0.82
Metal & Machi.	22.90	9.15	4.18	9.57	0	13.75	23.48	0.58
High-tech	20.98	9.45	5.62	5.93	0	11.55	21.35	0.37
				Western Region				
All	16.53	4.88	2.43	9.22	0	11.65	16.60	0.08
Processing	15.92	4.04	1.73	10.15	0	11.88	14.65	-1.26
Light Manuf.	15.33	4.85	2.24	8.24	0	10.48	16.10	0.77
Metal & Machi.	16.66	4.51	2.30	9.85	0	12.15	16.82	0.16
High-tech	21.40	7.52	6.11	1.69	6.09	13.88	20.80	-0.60
				Northeastern Region				
All	19.28	6.38	2.78	10.11	0	12.89	19.28	0.01
Processing	16.54	4.73	1.00	10.82	0	11.81	16.70	0.16
Light Manuf.	19.87	7.92	2.86	9.09	0	11.95	20.84	0.97
Metal & Machi.	21.30	6.52	3.70	8.31	2.77	14.78	20.42	-0.88
High-tech	16.61	5.03	2.52	9.06	0	11.58	16.49	-0.12

Note: The data of Guizhou and Tibet are removed from the estimation for the Western region.

Regional Analysis

The growth of industrial output may vary in different regions in China because of their difference in historical background and economic development. Using growth decomposition, we can examine the difference in the sources of output growth due to regional differences. We first apply the stochastic frontier model to the data set from each of the four main industrial groups in each region. And we try both time-varying decay and time-invariant technical inefficient models to each data set, and pick the result with a better fit from the two models. Table 5 reports the estimates of the chosen model for the four industrial groups in the four regions. For those data set with time-invariant technical inefficiency, the estimate of change in the technical efficiency is zero with $T\dot{E} = 0$.

Among the four regions, the Southern and Northeast regions have higher output growth (20.58% and 19.28%, respectively) than the Eastern and Western regions (16.74% and 16.53%, respectively). The high output growth in the Southern region is mainly due to high input growth and scale effect; the high output growth in the Northeastern region is due to high TFP growth. The growth of the Processing Industry is relatively lower than the growth of the other three industrial groups in the Southern region. The input growths in the other three industrial groups in the Southern region are all more than 9 percent and they experienced the highest input growths among all industrial groups and regions. The Northeastern region is where traditional heavy industries locate. With the improvement in technical inefficiency, the Metal and Machinery Industry in this region has the highest TFP growth among all different industrial groups and regions. The low output growth in the Western region is mainly caused by the low input growth. But, its high technical growth (9.22%) is only next to that of the Northeastern region (10.11%).

The relatively low output growth in the Eastern region is mainly due to low growth in the Processing Industry and Light Manufacturing Industry. Both input growth and TFP growth are relatively low for these two industrial groups. Another reason of the low industrial output growth in the Eastern region is mainly caused by the low output growth in several provinces, such as Beijing, Tianjin, Shanghai, Shanxi and Hubei. Beijing, being the capital, has a lowest estimated output industrial growth. Tianjin and Shanghai are port city-provinces heavily relied on commerce and exports. Both Shanxi and Hubei are inland provinces and their industrial output growths are not as fast as other Eastern provinces. There is, however, a clear sign of structural change in the Eastern region. The output growth of the Metal and Machine Industry in the

Eastern region is still relatively low compared to the Southern and Northeastern regions because of either low input growth or low TFP growth. Although the Eastern region does not have comparative advantages in the Metal and Machinery Industry when comparing with the Southern and Northeastern regions, its growth of the High-technology Industry remains high at 21.22 percent. The strong growth provinces in the Eastern region are the new industrial areas of Zhejiang, Anhui, and Shandong, which are supported by large input growth.

The improvement of technical efficiency has performed differently among the four regions. The Light Manufacturing Industry in the Southern region has shown a positive increase. In the traditional heavy industry Northeastern region, obviously the Metal and Machinery Industry has shown an improvement in technical efficiency. Both the Eastern and Western regions have shown a highest improvement in the High-technology Industry. The difference performance in the improvement of technical efficiency does reflect the comparative industrial advantages among the four regions.

V Conclusion

Armed with over three decades of economic reform since 1978, China's industrial exports by the turn of the 21st century have captured world attention. This article investigates into the factors that contribute to industrial output growth in different industrial groups and geographical regions in China. The empirical findings do provide an "X-ray" on industrial performance in China by identifying its strengths that show the various potentials and weaknesses that require additional improvements. Having achieved a high level of cheap labor-intensive manufacturing export, China should look into her next stage of industrial development if exports, especially in the high-end products, were to continue to provide overall economy vigor to economic development in China.

By using the more recent manufacturing industrial data and the appropriate proxy variables on physical capital and human capital, this article conducts a comprehensive study on the growth and productivity attributes for four main industrial groups, 29 two-digit industries, and four regions. Our growth decomposition method and regression results estimate the contributions from inputs growth, scale effect, technical progress, and technical efficiency changes to output growth. We found that labor has the largest cost share in the production, but its contribution to the input growth is the lowest, implying possibly the end of a low labor cost era in China's manufacturing. Human capital contributes about one-half of total input growth due to the large number of graduates from tertiary institutions. In terms of the output elasticity, the three inputs generate increasing returns to scale. This results in a positive scale effect for all the four groups of manufacturing industries and 29 two-digit industries. It contributes about 27 percent of the growth of TFP.

In our analysis, the growth of TFP is decomposed into scale effect, technical progress and technical efficiency changes. The contribution of technical progress to the output growth in the aggregates and three main industrial groups is close to, but about 1 percent – 3 percent higher than the contribution from input growth. The Metal and Machinery Industry has achieved the highest technical progress, while the High-technology Industry has lacked behind. Technical efficiency changes can only be found in the High-technology Industry and two two-digit industries in other industrial groups.

The structure change from light industries to heavy and high-technology industries is evident by the high output growth of the Metal and Machinery Industry and the High-technology. This transformation is mainly due to the high TFP growth. Both the Metal and Machinery Industry and the High-technology Industry have higher TFP growth than the Processing Industry and the Light Manufacturing Industry. In addition, the High-technology Industry dominates input growth due to a high input growth effect for labor and human capital.

In terms of regional growth, the Southern and the Northeastern regions have higher output growth than the Eastern and the Western region. The Southern region's high output growth is due to high input growth and scale effect. The high output growth in the Northeastern region is due to technical progress and technical efficiency change. The low industrial output growth in the Eastern region is mainly because some provinces are increasingly becoming services oriented and moved away from manufacturing.

Other than the performance of individual industry group and region, the macro picture is that China's industrial strength is based mainly in input growth, and the subsequent improvement in technical progress. These two factors probably explain the high quantity of Chinese manufacturing output and exports. The next challenge to industrial development in China will be the quality end, including efficiency change and promotion, and the appropriate development in human capital, in addition to other existing problems, such regional imbalance. Nonetheless, one has to take into account that China has gone far in the last three decades of reform, and the question is how China can extend its industrial and economic development qualitatively and comprehensively.

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Appendix:

Table A1 The Four Groups of Manufacturing Industries in China

1.	Processing Industry
131-139	Food and feed processing industry; Seed fat processing industry; Sugar industry; Slaughtering, meat and eggs processing industries; Aquatic products processing industry; Salt industry, and other food processing industry.
141- 149	Cakes, candy manufacturing; Dairy manufacturing; Canned food manufacturing; Fermentation products industry; Condiment manufacturing; and Other food manufacturing.
151- 159	Alcohol and alcohol beverage manufacturing sector; Soft drink manufacturing; Tea industry, and other beverage manufacturing.
161-169	Cured tobacco industry; Cigarette manufacturing, and other tobacco processing industry.
172-183	Cotton textile industry; Cotton textile industry; Wool textile industry, bast fibre manufacturing; Silk textiles; Knitwear industry; Other textiles; Apparel manufacturing; Hat industry; Shoemaking, and other fiber products industry.
191-195	Light leather industry; Leather products manufacturing; Tanning and fur industry; and Feather (down) and products industry.
2.	Light Manufacturing Industry
201- 204	Sawn timber, wood processing industry; Wood-based panel manufacturing; Wood products industry; and Bamboo, rattan, palm and grass products industry.
211-219	Wood furniture manufacturing; Bamboo, rattan furniture manufacturing industry; Metal furniture manufacturing; Plastic furniture manufacturing, and other furniture manufacturing.
221-223	Pulp manufacturing; Paper; and Paper products industry.
231-232	Printing industry; and Reproduction of recorded media.
241-249	Stationery Manufacturing; Sporting goods manufacturing; Musical instruments and other cultural goods industry; Toys manufacturing; Recreation equipment manufacturing, and other types of culture and education are not included in the sporting goods manufacturing.
251-257	Synthetic crude oil production industry; Crude oil processing industry; Petroleum products industry; and Coking industry.
261-268	Basic chemical raw materials manufacturing industry; Chemical fertilizer manufacturing; Chemical pesticides manufacturing; Organic chemical products manufacturing; Synthetic materials manufacturing; Special chemical products manufacturing; and Daily-use chemical products manufacturing.
271- 275	Chemicals manufacturing TC; Manufacturing chemical agents; Chinese herbal medicines and proprietary Chinese medicine industry; Animal drug manufacturing; and Biological products industry.
281-285	Cellulose fiber manufacturing; Synthetic fiber manufacturing industry; and Fishing gear and fishing gear materials manufacturing.
291-299	Tire manufacturing, hand cart tire manufacturing; Rubber board, tube, with the manufacturing sector; Rubber parts products industry; Reclaimed rubber manufacturing, gumboot manufacturing; Daily-use the rubber products industry; Renovation industry rubber, and other rubber products industry.
3.	Metal and Machinery
301-309	Plastic film manufacturing; Plastic plates, pipes, rods manufacturing; Plastic wire, rope and woven goods manufacturing; Foam and leather, synthetic leather manufacturing; Plastic packaging and containers manufacturing; Plastic shoes manufacturing; Daily-use sundry goods manufacturing plastics; Plastic parts and components industry, and other plastic products industry.
311-319	Cement manufacturing; Cement products and asbestos-cement products industry; Brick, lime and light manufacturing building materials; Glass and glass products industry; Ceramic

	products; Refractory products industry; Graphite and carbon products industry; and Mineral fibers and products industry not covered by other types of non-metallic mineral products industry.
321-326	Iron & Steel industry; Steel rolling processing industry; and Ferroalloy smelting industry.
331-336	Heavy non-ferrous metal smelting industry; Light non-ferrous metal smelting industry; and Non-ferrous alloys industry.
341-349	Manufacturing of metal structures; Cast iron pipe manufacturing; Tool manufacturing; Metal containers and packaging materials manufacturing, wirework & wirework industry; Fabricated metal products used in construction; Metal surface treatment and heat treatment industry; Ceramic manufacturing, and other fabricated metal products.
351-359	Boiler and prime mover manufacturing; Metalworking machinery manufacturing; General equipment manufacturing; Bearings, valves manufacturing; Other common parts manufacturing; Castings and forgings manufacturing; General mechanical repair industry, and other general machinery manufacturing.
361-368	Metallurgy, mining, mechanical and electrical equipment manufacturing industry; Petrochemical and other industrial equipment manufacturing; Textile industry equipment manufacturing; Agriculture, forestry, animal husbandry and fishery, water conservancy industry machinery manufacturing; Medical equipment manufacturing; Special equipment manufacturing industry; and Industry-specific machinery and equipment repair.
371-379	Railway transportation equipment manufacturing; Automotive; Motorcycle manufacturing; Bicycle manufacturing; Tram manufacturing; Ship manufacturing; Repair of transportation equipment industry, and other transportation equipment manufacturing industry.
4.	High-technology Industry
401- 409	Motor manufacturing industry; Transmission and distribution and control equipment manufacturing; Electrical equipment manufacturing; Household electrical appliances manufacturing; Lighting equipment manufacturing; Repair of electrical machinery industry, and other electrical machinery manufacturing industry.
411-419	Communications equipment manufacturing; Radio and television equipment manufacturing industry; Electronic computer manufacturing; Electronics manufacturing; Electronic components manufacturing; Daily-use electronic equipment manufacturing; Electronic devices and communications equipment repair industry, and other electronic equipment manufacturing.
421-429	Universal instruments manufacturing; Dedicated instrumentation manufacturing; Manufacturing of electronic measurement instruments; Measuring equipment manufacturing; Culture, office machinery manufacturing; Manufacture of watches; Instrumentation and culture, office equipment repair industry, and other instrumentation manufacturing.
431-439	Arts and crafts manufacturing; Daily-use sundry goods manufacturing; and Other supplies manufacturing.

Source: *Support System for China Statistical Application*, All China Marketing Research, Beijing.

Table A2 Number of Observations

	East	South	West	Northeast	Total
Processing	2,628	1,744	1,216	645	6,233
Light Manufacturing	3,671	2,232	1,311	814	8,028
Metal and Machinery	5,028	3,166	2,253	1,245	11,692
High-technology	1,965	1,068	424	402	3,859
Total	13,292	8,210	5,204	3,106	29,812

Note: The number of observations is based on 161 three-digit industries in 31 provinces from 1999 to 2007, excluding missing observations.