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Working Paper 2007-03
http://www.bus.lsu.edu/economics/papers/pap07_03.pdf

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The Dynamics of Provincial Growth in China: A Nonparametric Approach

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February 2007

Abstract

We use a recently developed non-parametric approach to analyze the variation in labor productivity growth across China's provinces. This approach imposes less structure on the data than the standard growth accounting framework and allows for a breakdown of labor productivity into capital deepening, efficiency gains, and technological progress. We find that capital deepening is the prime factor behind the change in the distributional dynamics of the labor productivity: on average capital deepening accounts for 75 percent of total labor productivity growth, while improvements in efficiency and technological progress account for 7 percent and 18 percent, respectively. We also find that while improvements in efficiency levels are higher in initially less productive provinces, relatively more productive provinces benefited more from technological progress than less developed ones.

JEL Classification: O1, O2, O3, O4, O53, and P2

Keywords: Provincial Growth in China, Labor Productivity, Convergence, Data Envelopment Analysis

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1 Introduction

Since the 1978 economics reforms, China's growth record has been impressive, but the contribution of its provinces to per capita income growth has been highly uneven.[1] Although average annual growth of real per capita GDP has picked up across all regions, coastal provinces have tended to grow faster than northern and western provinces. According to Aziz and Duenwald (2003), real GDP per capita in coastal provinces such as Fujian, Guangdong, and Zhejiang grew at an average annual rate of twice that of western provinces such as Gansu, Ningxia, and Qinghai during 1978-97. The dispersion of growth rates has not been purely a reflection of different stages of development. Indeed, among the initially poorer provinces those in the west have fallen further behind, while those at or near the coast have caught up with or even surpassed provinces that had the highest per capita incomes at the start of economic reforms. This uneven performance has been reflected in a growing income disparity across regions posing a key challenge to policymakers in Beijing.

Several studies investigating the differences in economic performance across China's provinces conclude no tendency toward *absolute* convergence in terms of real per capita GDP over the past two and a half decades. Bell, Khor, and Kochhar (1993) and Jian et al. (1996) find that income dispersion has declined between 1981 and 1990 as poorer provinces tended to grow faster than richer ones. When the sample period is extended, this result is not maintained. The absence of absolute convergence among China's provinces is in contrast with the behavior of US states, Japanese prefectures, and selected regions in western Europe, where absolute convergence appears to be the norm rather than the exception over extended periods of time (Barro and i Martin 2004).

However, there is evidence of *conditional* convergence with provinces converging to unique steady states distinguished by structural factors and preferential economic policies, which have been part of China's dual track approach to economic reforms. Démurger et al.

[1] Jian, Sachs, and Warner (1996), Li, Liu, and Rebelo (1998), Démurger et al. (2002), Dayal-Gulati and Husain (2002), and Aziz and Duenwald (2003).

(2002) find that, after controlling for openness and proximity to fast growing economies in East-Asia, growth in coastal provinces benefit significantly from preferential policies, which have fostered marketization and internationalization. Dayal-Gulati and Husain (2002) show that the prevalence of state-owned enterprises (SOEs) and a high ratio of bank loans-to-deposits—an indication of large directed lending—are often associated with lower growth. They also find that the coastal and north/northeastern regions were able to attract more FDI because of their relative prosperity and more developed infrastructure, which contributed to the high growth rates of these regions.

Previous studies explore the dynamics of provincial growth using the augmented Slow model. However, in this paper, we examine the evolution of three components of labor productivity growth: efficiency gains (movements toward the production frontier), technological progress (outward shifts of the production frontier), and capital deepening (movements along the production frontier). This decomposition allows us to investigate how the dynamics of each component affect the growing income disparity across provinces.

For our analysis we use a recently developed non-parametric technique known as Data Envelopment Analysis (DEA). For a given date in our sample period we construct a production frontier for China, as a whole, using all observed input-output combinations at the province level. The inputs are capital and labor, and the output is GDP. After identifying the frontier, we can measure the efficiency level of each province with respect to the frontier. Having determined the evolution of capital-labor ratios and efficiency indices for each province, we can derive the contribution of technological progress to labor productivity growth in each province.

DEA was developed by Farrell (1957) and Afriat (1972), and was further extended by Färe et al. (1994, 1995) and Kumar and Russell (2002).[2] Our approach is similar to that of Kumar and Russell (2002), except that in constructing the production possibility frontier

[2]Färe et al. (1994) use DEA to analyze the productivity growth in 17 OECD countries, while Kumar and Russell used the same technique with a different decomposition of labor productivity to analyze the productivity performance across 57 countries in the world.

at time t we follow Diewert (1980) by using all data available up to time t, rather than just the observations at time t. This modification prevents technology from regressing, an unrealistic feature in the Kumar and Russell (2002) findings. Using DEA has several advantages over standard growth accounting. First, in this approach the production frontier is directly constructed from the data. Hence we do not have to impose any restrictions other than a functional form that satisfies a constant returns to scale technology. Second, our approach allows us to identify separately the contributions of efficiency and technological improvements to productivity growth. Finally, our approach does not impose any kind of structure on markets, whereas in the standard growth accounting framework it is assumed that markets are competitive. This assumption is possibly critical in the case of China, where government regulation of markets is still extensive.

Our results can be summarized as follows. First, labor productivity growth in China's provinces has largely been driven by capital deepening. In particular, we find that on average capital deepening accounts for about 75 percent of total labor productivity growth, while efficiency and technological improvements account for about 7 percent and 18 percent, respectively. Second, the capital deepening is also the driving factor behind the changes in the *distributional dynamics* of the labor productivity over the last two decades –the initial distribution of labor productivity has unimodal shape, while its 1998 distribution has new peaks. Finally, while improvements in efficiency levels are higher in initially less productive provinces, relatively more productive provinces benefited more from technological progress than less developed ones.

The rest of the paper is organized as follows. Section 2 explains the construction of the country-wide production frontier along with the calculation of efficiency levels and demonstrates how we decompose labor productivity into the three components described above. In section 3, we present our results and discuss their implications. Section 4 offers some concluding remarks.

2 Theoretical Framework

Let $\mathbf{Z}_t = (K_t, L_t)$ denote a bundle of capital-labor inputs to produce a single output Y_t at time t. We denote this single output technology by means of a production function F_t that gives the maximum amount $F_t(\mathbf{Z}_t)$ of output that can be produced using input amounts $\mathbf{Z}_t$. This production technology gives rise to the production set:

$$\tilde{\mathcal{P}}_t = \left\{ (\mathbf{Z}_t, Y_t)' \in \mathbb{R}^3_+ : \ F_t(\mathbf{Z}_t) - Y_t \geq 0 \text{ and } \mathbf{Z}_t \geq \mathbf{0} \right\}. \tag{1}$$

The set of boundary points of $\mathcal{P}_t$ is called the production (or transformation) frontier, which we shall denote by $\tilde{\mathcal{F}}_t$ and is completely characterized by production function F_t; that is, $(K_t, L_t, Y_t) \in \tilde{\mathcal{F}}_t$ if and only if $F_t(K_t, L_t) = Y_t$. With these definitions, any input-output combination in the interior of the production set represents an inefficient transformation of $\mathbf{Z}_t$ into Y_t and the distance between such a combination and boundary will be a measure of the level of inefficiency. Thus, in order to measure the scale of inefficiency, it is important to identify the production frontier.

In this paper, we confine ourselves to constant returns to scale (CRS) production technologies, i.e. F_t is a CRS production function. With this assumption, $F_t(K_t, L_t) = Y_t$ can be rewritten as $f_t(k_t) = y_t$, where $k_t = K_t/L_t,\ y_t = Y_t/L_t$, and $f_t(k_t) = F_t(K_t/L_t, 1)$. With this transformation, the transformed production set is described by

$$\mathcal{P}_t = \left\{ (k_t, y_t)' \in \mathbb{R}^2_+ : \ f_t(k_t) - y_t \geq 0 \text{ and } k_t \geq 0 \right\}. \tag{2}$$

Note that when F_t exhibits CRS, f_t exhibits non-increasing returns to scale (NIRS).

As discussed in the introduction, our approach to constructing production sets (and frontiers) is data-driven. Roughly speaking, we define the production set at time t as the smallest convex set that envelopes all available data at time t. The boundary of this set will represent the production frontier. Formally, the production frontier is constructed from the data as follows.

$$\mathcal{F}_t = \left\{ (k_t, y_t)' \in \mathbb{R}^2_+ : \; y_t \leq \sum_{\tau=1}^{t} \sum_{i=1}^{I} \theta^i_\tau y^i_\tau, \; \sum_{\tau=1}^{t} \sum_{i=1}^{I} \theta^i_\tau k^i_\tau \leq k_t, \; \theta^i_\tau \geq 0, \text{ and } \sum_{\tau=1}^{t} \sum_{i=1}^{I} \theta^i_\tau \leq 1 \right\}, \quad (3)$$

where θ^i_τ's represent "weights" and $(k^i_\tau, y^i_\tau)'$ represents the intensive form of the input-output vector of province i at time τ. As Kumar and Russell (2002) noted, this construction implies that each point in the production set is either a linear combination of observed points or a point dominated by a linear combination of observed points.[3] By imposing the restriction $\sum_{\tau=1}^{t} \sum_{i=1}^{I} \theta^i_\tau \leq 1$, we make the production technology exhibit NIRS (Afriat 1972). Note that this production technology also satisfies the free-disposal condition, that is inputs and output can be disposed of at no cost. It is important to emphasize that in constructing the frontier we follow Diewert (1980) in that we use all available data up to time t. This approach is different from the one developed by Kumar and Russell (2002) and Färe et al. (1994), who construct the frontier by only using the input-output data observed at time t. We incorporated previous observations to prevent the possibility of technological regress.[4]

Given the production frontier $\mathcal{F}_t$, we are now ready to describe how to calculate efficiency indexes. For a given point $(k_t, y_t)' \in \mathcal{P}_t$, following Farrell (1957), we define the output-based (or Farrell) efficiency function as follows:

$$E_t(k_t, y_t) = min\{\lambda : \; (k_t, y_t/\lambda)' \in \mathcal{P}_t\}. \quad (4)$$

In words, this function is defined as the inverse of the maximum proportional amount that labor productivity y_t can be expanded, while remaining in the production set $\mathcal{P}_t$, given the capital intensity k_t. For each province i, we calculate the efficiency index λ^i_t at time t by solving the following linear programming problem:

[3] For an excellent discussion of the construction of production frontiers and DEA, see Farrell (1957), Afriat (1972), and Färe et al. (1995). In particular, Färe et al. (1995) give a comprehensive account of various extensions of DEA.

[4] Nothing suggests that China has experienced a decline in its technological knowledge since it started economic reforms. Hence, the technology that was available at date t was at least as advanced as the technology available at date $s < t$. However, our method is data driven and by not including previous observations it could produce an estimate of the production set at date t, which does not include all the elements in the production set at date $s < t$.

$$Min_{\lambda_t^i, \theta_1^1, \ldots, \theta_t^I} \quad \lambda_t^i \tag{5}$$

subject to

$$\begin{aligned} y_t^i/\lambda_t^i &\leq \sum_{\tau=1}^{t}\sum_{j=1}^{I} \theta_\tau^j y_\tau^j \\ k_t^j &\geq \sum_{\tau=1}^{t}\sum_{j=1}^{I} \theta_\tau^j k_\tau^i \\ 1 &\geq \sum_{\tau=1}^{t} \theta_\tau^i \\ \theta_\tau^j &\geq 0, \qquad \tau = 1, \ldots, t, \text{ and } j = 1, \ldots, I. \end{aligned}$$

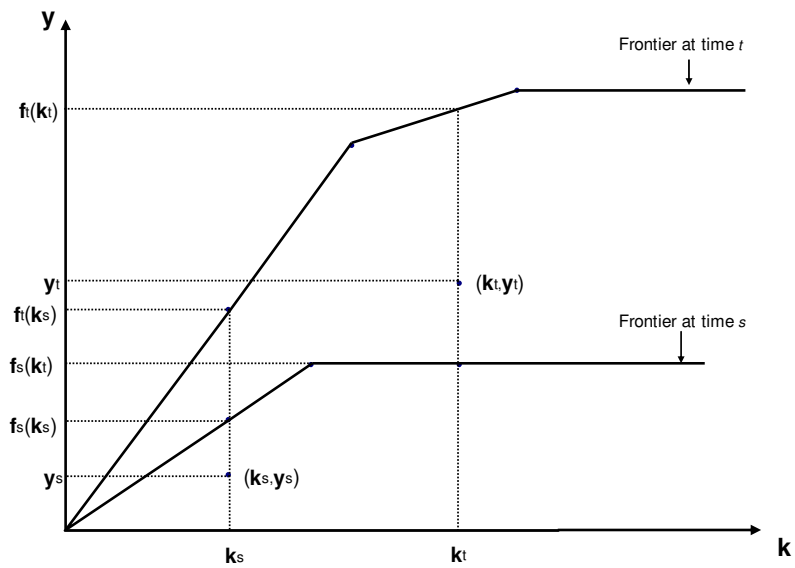
Having calculated the efficiency indexes we can decompose productivity growth into efficiency, technological change, and capital deepening components as in Kumar and Russell (2002).[5]

To illustrate the decomposition of output per worker, Figure 1 depicts two production sets for time periods s and t, with $s < t$. Points (k_s, y_s) and (k_t, y_t) represent the input-output combinations of the same economy in periods s and t, respectively. Note that these observed input-output combinations are in the interiors of the corresponding production sets, hence, they are inefficient. Given k_s units of input, under the production technology available at time s, this economy can produce at most $f_s(k_s) = y_s/\lambda_s$ units of output, where λ_s is the efficiency index for the observed production. Similarly, when the input level is k_t, the maximum amount of output that can be produced, under the production technology available at time t, is $F_t(k_t) = y_t/\lambda_t$, where λ_t is the efficiency index for the observed production in period t. The combination of these two observations yields

$$\frac{y_t}{y_s} = \frac{\lambda_t \times f_t(k_t)}{\lambda_s \times f_s(k_s)}. \tag{6}$$

[5] Färe et al. (1994) propose a different method involving the decomposition of the (Malumquist) productivity index into technical change, pure efficiency change, and scale change. We chose to follow the method in Kumar and Russell (2002) because it allows us to assess the role of capital deepening in productivity growth.

Figure 1: Decomposition of output per worker



Multiplying the numerator and denominator on the right hand side by $f_s(k_t)$, which is the maximum output that can be produced with input level k_t under the first period production technology, and rearranging terms we obtain

$$\frac{y_t}{y_s} = \frac{\lambda_t}{\lambda_s} \times \frac{f_t(k_t)}{f_s(k_t)} \times \frac{f_s(k_t)}{f_s(k_s)}. \tag{7}$$

The left hand side of this equation represents the change in output per worker between periods s and t. The first term on the right hand side represents the change in efficiency over these two periods. The second term represents the shift in the production frontier at capital intensity of k_t. The last term represents the change in maximum output per worker owing to the change in capital intensity between the two periods. Thus, identity (5) decomposes labor productivity into three components: change in efficiency change, change in technology, and change in capital intensity. Note that this is not the only way to decompose output per worker. Considering again equation (6), multiplying the numerator and denominator on the right hand side by $f_t(k_s)$, which is the maximum output that can be produced with input level k_t under the first period production technology, and rearranging terms we get

$$\frac{y_t}{y_s} = \frac{\lambda_t}{\lambda_s} \times \frac{f_t(k_s)}{f_s(k_s)} \times \frac{f_t(k_t)}{f_t(k_s)}, \tag{8}$$

where each term on the right hand side is interpreted in the same way as in equation (7). Note that unless the production technology F is Hicks neutral, there is no reason to expect that $\frac{f_t(k_s)}{f_s(k_s)}$ equals $\frac{f_t(k_t)}{f_s(k_t)}$. Hence, we have two different representations of technical change (and of the change in potential output owing to the change in capital intensity, that is the third term in equations 7 and 8). Following Caves et al. (1982), Färe et al. (1994), and Kumar and Russell (2002), we avoid having two arbitrary decompositions of output per worker by considering the geometric mean of the right hand sides of (7) and (8):

$$\frac{y_t}{y_s} = \frac{\lambda_t}{\lambda_s} \times \left(\frac{f_t(k_t)}{f_s(k_t)}\frac{f_t(k_s)}{f_s(k_s)}\right)^{1/2} \times \left(\frac{f_s(k_t)}{f_s(k_s)}\frac{f_t(k_t)}{f_t(k_s)}\right)^{1/2}. \tag{9}$$

Taking the logarithms of both sides of (9) and dividing by $t-s$ (number of years between two periods), we have

$$g_y = g_{eff} + g_{tech} + g_{cap}, \tag{10}$$

where g_y represents the average annual growth rate of output per worker, and g_{eff}, g_{tech}, g_{cap} are the average annual growth rate of efficiency index, the average annual growth rate of technical progress, and the average annual growth rate of the potential outputs (due to the change in capital intensity) between two periods, respectively. This completes the theoretical framework of our approach. Before moving further, let us recap briefly what we have introduced in this section. We started with the construction of a production frontier from the observed data. Then we showed how to measure the associated (in)efficiency indexes by solving the corresponding linear programming problem. Finally, we illustrated how, after having calculated the efficiency indexes, growth in output per worker can be decomposed into changes in efficiency, technology, and capital intensity.

Several remarks are in order. First, the production frontier is constructed from the data and consequently it is defined relative to the best technology of the provinces in our

sample. Thus, this frontier may be below the true frontier, which in turn implies that the efficiency indexes represent lower bounds of true inefficiencies. In the standard growth accounting framework the true frontier is also not known, but in that framework each province's performance is compared only with its previous-year performance, not with a common benchmark across all provinces. Moreover, since we want to compare the relative performance of the provinces, we think that our non-parametric approach is more suitable.[6] Second, our approach allow for the separation of changes in efficiency from technological progress. In the standard growth accounting approach, each province is assumed to be on "its" own frontier, hence it is impossible to make the same separation. Third, in development accounting framework calculation of TFP levels requires that technological progress is Hicks-neutral, which we did not have to assume in our analysis. Indeed, our analysis in the next section suggests that technological progress is not Hicks-neutral. Finally, and more importantly, in calculating productivity growth rates we did not impose any condition on market behavior, while in growth accounting TFP is derived under the assumption that markets are competitive. To illustrate this point consider the following production function

$$Y(t) = F(K(t), L(t), t),$$

where t represents an index of technology at time t. Taking the logarithm of both sides, differentiating with respect to time, and rearranging the terms, we obtain

$$g_A = g_Y - \epsilon_K g_K + \epsilon_L g_L,$$

where ϵ_K and ϵ_L are elasticity of capital and labor with respect to output and g_X denotes the growth rate of the variable X. In practice, we do not know these elasticities. To overcome this difficulty it is assumed that (i) F exhibits CRS, which we also assumed, and (ii) markets are competitive, which implies that the labor elasticity can be replaced with the share of

[6] Our approach does not take into account possible measurement errors. There is an alternative technique, known as the stochastic frontier approach, to calculate the efficiency indexes under possible measurement errors. We did not consider this approach in our study, since its implementation imposes additional restrictions on the functional form of the frontier and error terms.

labor in total output. For advanced countries with considerable market competition, it may be reasonable to use the labor share as a proxy for ϵ_L, but in the case of China, where many product and factor markets remain heavily regulated, this is obviously more problematic. DEA therefore seems a more suitable approach for analyzing productivity growth in China's provinces than the standard growth accounting framework.[7]

3 Empirical Analysis

We calculate labor productivity growth and efficiency levels for a sample of 28 provinces between 1978 and 1998. Value added and investment data are from the provincial yearbook of China.[8] Labor data are from Young (2000), who compiled the data from provincial yearbooks, *A Compilation of Historical Statistics* (State Statistical Bureau, 1990), and Hsueh, Li and Liu (n.d.). More detailed information about data sources and the construction of variables is provided in the appendix.

Before turning to the discussion of efficiency indexes, it will be interesting to look at the dynamics of productivity change across provinces. All provinces record increases in labor productivity between 1978 and 1998 (Table 1). The average annual growth rate for all provinces is 7.2 percent over this period, but productivity performances vary substantially between subsets of provinces. While labor productivity in the coastal provinces of Fujian, Guangdong, Jiangsu, and Zhejiang grows at an annual rate of about 10 percent, labor productivity in the landlocked provinces of Heilongjiang, Gansu, and Qinghai grows at an average annual rate of only 4-5 percent.[9] In 1978, the coastal provinces are on average less productive than the landlocked provinces. In a ranking of provinces by level of labor

[7] We were confronted with two additional problems. First, for most of the provinces we did not have data on labor compensation. Second, for the provinces where data were available, the labor shares were very small, an issue that was also noted by Young (2005) who used data from other auxiliary sources to correct for potential measurement errors in labor shares.

[8] Hainan and Tibet Autonomous Region were excluded for lack of data on value-added and fixed-capital investment. We restricted our sample over the period of 1978-1998, because we did not have a comparable labor data for recent years.

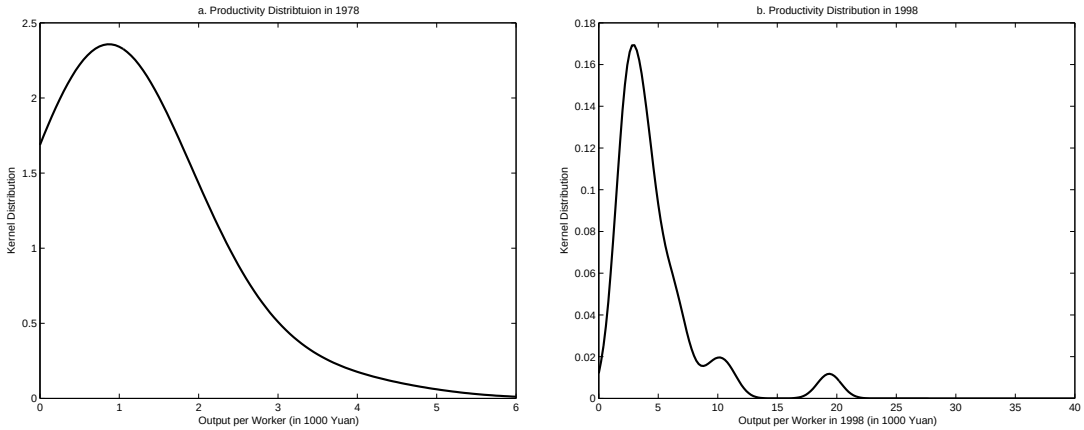
[9] Aziz and Duenwald (2003) report qualitatively similar results for comparisons of per *capita* GDP across provinces.

Table 1: Labor Productivity and Efficiency in 1978 and 1998

Province	*Output per Worker*		*Efficiency Index*	
	y_{1978}	y_{1998}	λ_{1978}	λ_{1998}
Beijing	2451	10806	0.969	0.894
Tainjin	2254	9564	0.843	0.859
Hebei	868	4049	0.687	0.759
Shanxi	912	3392	0.517	0.637
Inner Mongolia	889	3619	0.594	0.671
Liaoning	1828	6247	0.918	0.794
Jiling	1270	4213	0.710	0.758
Heilongjiang	1736	4404	1.000	0.732
Shanghai	3907	19367	1.000	1.000
Jiangsu	897	7300	1.000	0.906
Zhejiang	689	5906	0.658	0.865
Anhui	608	2644	0.859	0.754
Fujian	718	5358	0.723	0.949
Jiangxi	694	2942	0.601	0.761
Shandong	759	3864	0.778	0.782
Henan	580	2618	0.585	0.694
Hubei	790	4433	0.654	0.846
Hunan	645	2292	0.826	0.804
Guangdong	817	6402	0.611	0.871
Guanxi	521	1974	0.576	0.723
Sichuan	580	2323	0.437	0.645
Guizhou	442	1474	0.460	0.534
Yunnan	526	1981	0.443	0.563
Shaanxi	754	2677	0.500	0.559
Gansu	933	2248	0.573	0.631
Qinghai	1074	2397	0.541	0.558
Ningxia	959	2849	0.590	0.641
Xingiang	794	4007	0.541	0.697
Mean	1068	4691	0.686	0.746
Std Dev.	752	3662	0.178	0.127

Sources: Provincial Yearbooks of China and authors estimates
Note: Capital intensity (capital per worker) and labor productivity (labor per worker) are in terms of Yuan per worker.

Figure 2. Provincial Productivity Distributions in 1978 and 1998



productivity in 1978, with the most productive province at rank 1, Fujian, Guangdong, and Zhejiang rank 17th, 12th, and 16th, respectively, while Qinghai and Gansu rank 8th and 10th, respectively. However, the coastal provinces did not just catch up with the initially more productive landlocked provinces, they surpassed them: as by 1998, Fujian, Guangdong, and Zhejiang rank 8th, 5th, and 7th, respectively, while Qinghai and Gansu rank 22th and 25th, respectively. Although the difference in average growth rates between these two groups of provinces is consistent with their initial levels of labor productivity, there is no convergence in the mean across whole China.[10] To provide a better understanding of the dynamics, in Figure 2a and 2b we plot the (kernel) distributions of productivity levels in 1978 and 1998.[11] In 1978 overall distribution has a unimodal shape; while it has new peaks in 1998. Our purpose is to identify the factors that are responsible for this change in overall distribution.

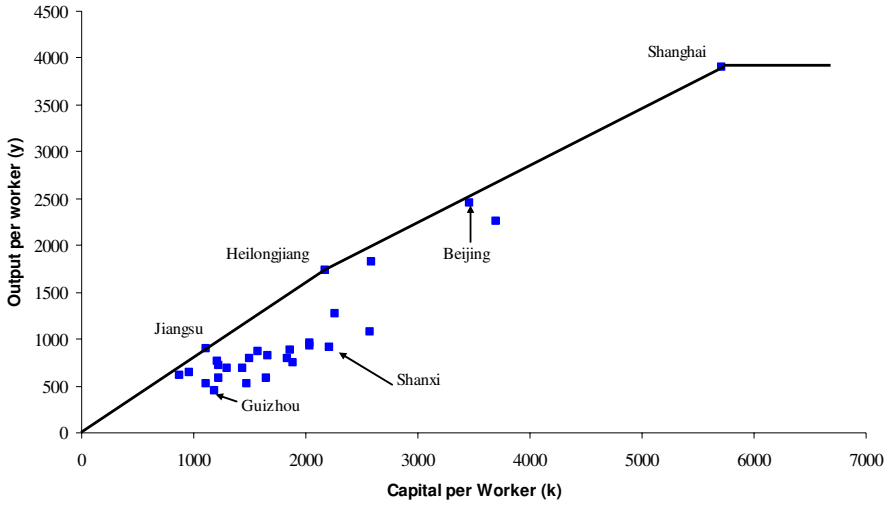
Turning now to the efficiency indexes reported in Table 1,[12] we note that Heilongjiang,

[10] We formally tested for absolute convergence in labor productivity across provinces by running the regression $g_y^i = \beta_0 + \beta_1 \ln(y_{1978}^i) + \varepsilon^i$, where g_y^i denotes the average annual growth rate of labor productivity of province i between 1978 and 1998 and ε^i is the associated error term. The estimate of β_1 is -0.0038 and is insignificant with a standard error of 0.0047.

[11] More information on the construction of Kernel distributions are provided in Appendix B.

[12] These results are (slightly) different from our earlier results in the IMF working paper, because here capital stocks are constructed using longer investment series, which makes estimates more reliable (see appendix A).

Figure 3.a. Production set and frontier, 1978



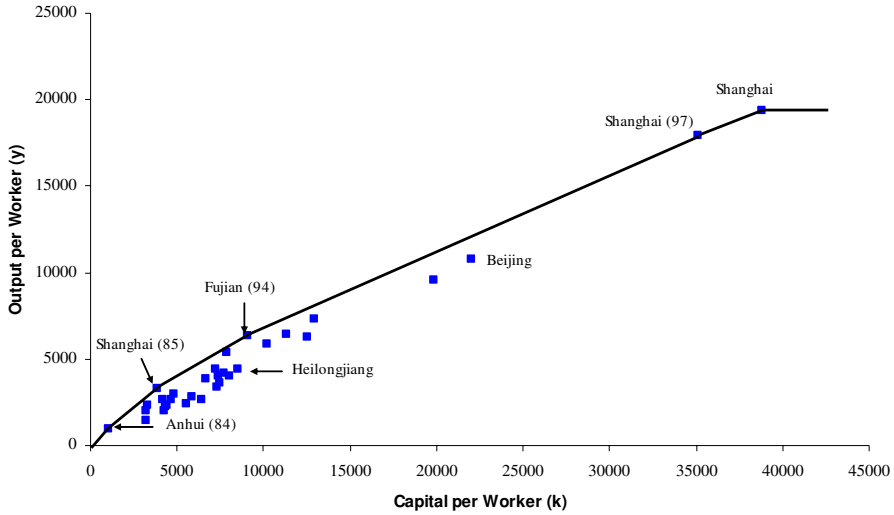
Jiangsu, and Shanghai have efficiency indexes of 1 in 1978.[13] This result implies that our non-parametric approach excluded 25 provinces from the technology frontier. Figure 3.a illustrates the positions of the provinces relative to the technology frontier in 1978 and suggests considerable dispersion of production activities.

The last column of Table 1 reports the efficiency indexes in 1998. In that year, only Shanghai has an efficiency index of 1.[14] Figure 3.b represents the production set and its frontier in 1998. The frontier is shaped by the input-output combinations of Anhui in 1984, Fujian in 1994, Shanghai in 1985, 1997, and 1998. To clearly show the relative positions of the provinces in 1998, we excluded all other previous observations in the interior of the production set. Compared with the Figure 3.a, we note that production activities are generally closer to the frontier in 1998 than in 1978. Indeed, the average efficiency index for all provinces increased from 0.686 in 1978 to 0.746 in 1998, while the standard deviation declined from 0.178 to 0.128 over the same period. These trends suggest convergence both

[13]The efficiency indexes are calculated by solving the linear programming problem (5) for 1978 and 1998. In 1978 we have only 28 observations. In 1998, however, we have 588 observations (28 for each year over 21 years).

[14]We have calculated these statistics for each year and we found that Shanghai always remained on the frontier. These results are available from the authors upon request.

Figure 3.b. Production set and frontier, 1998



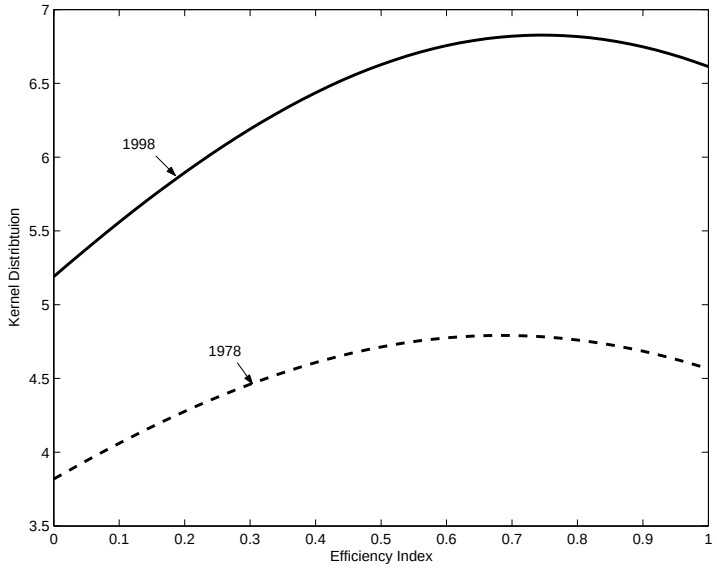
in the mean and the standard deviation of efficiency indexes across provinces over 1978-98.[15] At this point it is important to notice that the technical progress has not shifted the frontier by the same proportion at each capital-labor ratio. For example, between 1994 and 1998 the lower part of the frontier remained the same. This simply implies that the technical progress has not been Hicks-neutral.

Figure 4 illustrates the kernel distributions of efficiency indexes in 1978 and 1998. Two important points emerge from this figure. First, note that there is a (weak) shift in the distribution towards 1 between 1978 and 1998. This shift further confirms the convergence over this period. Second and more importantly, the shapes of the distributions are mostly the same in both years, which suggest that efficiency *can not* be a driving factor for the change in the shape of productivity distribution between 1978 and 1998 (see Figure 2).

To determine which factor has played the most significant role on provincial growth dynamics, we now turn to the decomposition of labor productivity into capital deepening,

[15] Similar to the labor productivity case, to test for absolute convergence in efficiency across provinces we run the regression $g^i_\lambda = \beta_0 + \beta_1 \ln(\lambda^i_{1978}) + \varepsilon^i$, where g^i_λ denotes the average annual growth rate of efficiency index of province i between 1978 and 1998 and ε^i is the associated error term. The estimate of β_1 is -0.0243 and is significant with a standard error of 0.0042, supporting our contention of absolute convergence in efficiency indexes.

Figure 4. Provincial Efficiency Distribution in 1978 and 1998



efficiency gains, and technological progress. Table 2 shows the results of this decomposition and the relative contributions of the three factors to productivity growth between 1978 and 1998. Note that average productivity growth is 7.2 percent of which 5.2 percentage points are contributed by capital deepening. Thus, about 75 percent of productivity growth across China's provinces is explained by capital deepening, with technical progress and efficiency changes accounting about 18 and 7 percents, respectively, of the productivity growth.[16] The high contribution of capital accumulation to labor productivity growth is consistent with the standard growth accounting studies of the sources of overall GDP growth in China (Chow (1993), Chow and Li (1999), and Heytens and Zebregs (2003); and with studies of the sources of GDP growth in other East-Asian economies (Young 1995).

Although on average most of the productivity improvement is attributable to capital deepening, provincial level decompositions show some different trends. We find, for example, that the relative contribution of capital deepening to average annual labor productivity growth in Heilongjiang, Anhui, Hunan, and Shandong during 1978-1998 is at least 90 per-

[16]This conclusion remains mostly the same when we even consider sub periods. Between 1978 and 1990, for example, about 78 percent of countrywide productivity growth is explained by capital deepening. Contributions of technical progress and efficiency changes, on the other hand, are about 13 and 9 percents, respectively. These results are available upon request.

Table 2: Decomposition of Labor Productivity Growth, 1978-1998

	Productivity Growth	*Change in Efficiency*	*Change in Technology*	*Capital Deepening*	**Relative Contribution of**		
Province	g_y	g_{eff}	g_{tech}	g_{cap}	*Efficiency*	*Technology*	*Capital*
Beijing	7.4	-0.4	3.2	4.6	-5.4	43.5	61.9
Tainjin	7.2	0.1	3.0	4.1	1.3	42.1	56.6
Hebei	7.7	0.5	1.0	6.2	6.5	13.4	80.1
Shanxi	6.6	1.0	1.0	4.6	15.9	15.2	68.9
Inner Mongolia	7.0	0.6	1.0	5.4	8.7	14.8	76.5
Liaoning	6.1	-0.7	2.0	4.8	-11.8	33.2	78.6
Jiling	6.0	0.3	1.1	4.6	5.5	18.6	75.9
Heilongjiang	4.7	-1.6	1.3	4.9	-33.5	27.9	105.6
Shanghai	8.0	0.0	4.3	3.7	0.0	53.6	46.4
Jiangsu	10.5	-0.5	2.1	8.9	-4.7	20.0	84.7
Zhejiang	10.7	1.4	1.7	7.6	12.7	15.5	71.8
Anhui	7.3	-0.7	0.7	7.3	-8.9	9.8	99.1
Fujian	10.0	1.4	1.2	7.4	13.5	11.8	74.6
Jiangxi	7.2	1.2	0.6	5.5	16.3	8.1	75.5
Shandong	8.1	0.0	0.9	7.2	0.3	10.6	89.1
Henan	7.5	0.9	0.6	6.0	11.3	8.3	80.4
Hubei	8.6	1.3	1.0	6.3	14.9	11.3	73.8
Hunan	6.3	-0.1	0.7	5.7	-2.1	11.0	91.2
Guangdong	10.3	1.8	1.8	6.7	17.2	17.7	65.1
Guanxi	6.7	1.1	0.7	4.9	17.1	9.9	73.0
Sichuan	6.9	1.9	0.6	4.4	28.1	8.9	63.0
Guizhou	6.0	0.7	0.6	4.7	12.4	10.8	76.8
Yunnan	6.6	1.2	0.6	4.8	18.1	9.7	72.2
Shaanxi	6.3	0.6	0.8	4.9	8.8	11.9	79.3
Gansu	4.4	0.5	0.6	3.3	11.0	14.0	75.0
Qinghai	4.0	0.2	0.6	3.2	3.9	14.7	81.4
Ningxia	5.4	0.4	0.5	4.5	7.6	9.9	69.5
Xingiang	8.1	1.3	1.2	5.6	15.7	14.9	69.5
Mean	7.2	0.5	1.3	5.4	7.0	18.0	75.0

Sources: Provincial Yearbooks of China and authors estimates based on equations (9) and (10).

cent, while it is less than 65 percent in Beijing, Tianjing, Sichuan, and Shanghai. We also see that while changes in the technical progress have important contributions to productivity growth in Beijing, Tianjing, Liaoning, Heilongjiang, and in particular, Shanghai; in Jiangxi, Guanxi, Sichuan, and Yunnan improvements in efficiencies have more significant effect than technical progress on productivity growth.

At this point it will be interesting to investigate the effects of each factor on the distributional dynamics of labor productivity. To isolate the effects of changes in efficiency on the initial productivity distribution, we construct counterfactual labor productivity, y_E, in 1998 by multiplying each labor productivity observation in 1978 by the corresponding change in the efficiency index over 1978-98, i.e. $y_E \equiv (\lambda_{98}/\lambda_{78}) \times y_{78}$. The kernel distribution of y_E is shown by the dashed-line in Figure 5 and notice that this transformation did not change the unimodal shape of the labor productivity distribution in 1978 (compare with Figure 2.a). To see the effect of technical progress, we further multiply y_E by the second term in (10). This effect is illustrated by the solid-line in Figure 5. This operation has shifted the distribution down and made the tail of distribution ticker, but the shape of distribution remains mostly unchanged. This analysis shows that the capital-deepening is also the driving factor on changes in the *distributional* dynamics of labor productivity. Indeed if we multiply the second distribution by the last term (i.e. capital-deepening) in (10) we will obtain Figure 2.b.

An important remaining question is whether there is any systematic relationship between the growth rates of the three components of labor productivity growth and the initial level of labor productivity. To investigate this, we regressed the average annual growth rate of each variable on initial labor productivity along with other variables that might have possible effects on these growth rates.[17] The regression results are presented in Table 3.

[17]Two caveats need to be emphasized. First, we have only 28 observation which make estimates less precise. Second, the causality may run in the other direction as well. For example, initially more efficient provinces might attract more domestic and foreign investment. The best way to address the second issue is to use instrumental variables approach. Unfortunately, there is no good instrument to control this reverse effect.

Figure 5. Counterfactual Productivity Distributions in 1998

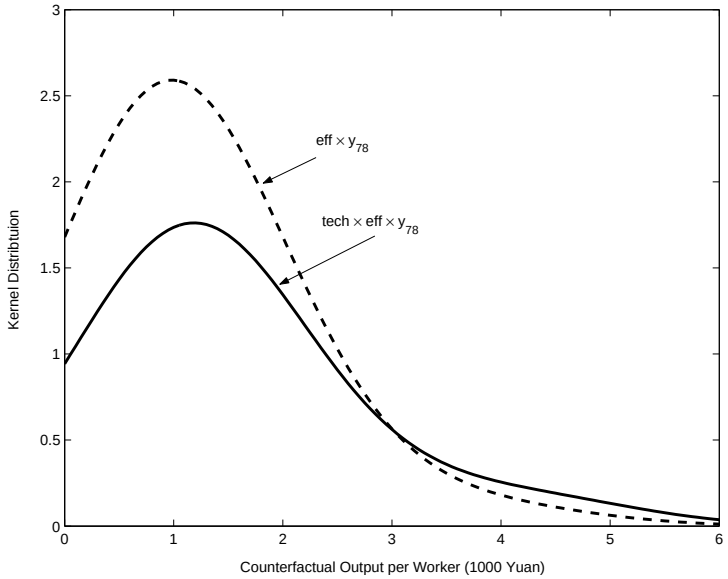


Table 3. Regression Results

	Dependent Variable			
	g_y	g_{eff}	g_{tech}	g_{cap}
	(1)	(2)	(3)	(4)
Inv/GDP	0.380*	0.161*	0.106**	0.116
	(0.123)	(0.046)	(0.055)	(0.086)
FDI/GDP	-0.016	0.068	0.012	-0.098
	(0.075)	(0.046)	(0.021)	(0.059)
Coastal Dummy	0.014**	-0.002	0.004	0.012**
	(0.008)	(0.004)	(0.002)	(0.007)
$ln(y_{78})$	-0.011*	-0.011*	0.013*	-0.013*
	(0.004)	(0.003)	(0.002)	(0.004)
Adj. R^2	0.435	0.363	0.786	0.354

Notes: There are 28 observations and numbers in parentheses represent the (robust) standard errors. * (**) means the corresponding coefficient is significant at the 5% (10%) level.

Column 1 represents results where the dependent variable is labor productivity. Here the costal dummy is significant at the 10% level, while the FDI/GDP and initial productivity level are significant at 5%. Given that the coefficient of the initial labor productivity is negative and significant supports the conditional convergence hypothesis. There is a positive and significant correlation between FDI and labor productivity growth which is in line with Zebregs (2003) results. Column 2 shows the results when the dependent variable is the average annual growth rate of efficiency index. The coefficient of the initial productivity is negative and statistically significant. This suggests that improvement in efficiency was higher in initially less advanced provinces than in richer ones, which is consistent with our earlier observation. We also see that FDI had a positive and significant effect on efficiency growth. When we regressed change in technology on the initial productivity level and other control variables, we found that coefficient of the initial productivity is positive and statistically significant (see Column 3). This suggests that initially more productive provinces have benefited more from technological progress than less developed provinces. This result is in support of theories of technological diffusion that conjecture that the cost of adopting new technologies declines with the level of economic development or the abundance of human capital in the receiving location.[18] It is also interesting to note that the coefficient of FDI is positive and statistically significant. Finally, Column 4 represents results when the dependent variable is the growth rate of capital deepening. The negative and significant coefficient of the initial labor productivity suggests that capital deepening was higher in initially less developed provinces. Surprisingly, neither FDI nor domestic investment had any significant effects on the growth rate of capital deepening.

4 Conclusion

We have used a recently developed non-parametric approach to decompose labor productivity growth in China's provinces into three components: capital deepening, efficiency gains,

[18] See for example Nelson and Phelps (1966) and Findlay (1978).

and technological progress. This decomposition has allowed us to investigate the contribution of each of the three factors to the pattern of productivity growth across provinces. We find that capital deepening is by far the biggest source of labor productivity growth in China's provinces between 1978 and 1998. We also find that capital deepening is the prime factor for the change in the dynamics of labor productivity.

Efficiency is improved between 1978 and 1998, especially in the initially least productive provinces which often has the largest agricultural sectors. The efficiency gains are almost certainly a reflection of China's economic reforms, which have facilitated a profound transformation of the country's economic structure, including a large reallocation of labor from unproductive farming and state-owned enterprises to more productive industries in the non-state sector.

Technological progress was generally largest in the initially more productive provinces in line with theories of technological diffusion. Perhaps somewhat surprisingly, technological progress in the coastal provinces, which recorded the largest inflows of FDI, was not noticeably higher than in other provinces. A possible explanation is that FDI in the coastal provinces did not introduce important new technologies because it was concentrated in low-tech sectors or did not have significant spillovers to the rest of the local economy.

A Data Appendix

This appendix provides additional information about our data sources and the construction of capital stocks. We obtained provincial level output (GDP) data from various issues of the *Statistical Yearbook of China*.

Labor data reported in the *Statistical Yearbook of China* contain large swings and do not take into account the possible change in employment due to migration between provinces. For example, according to the reported series there was a substantial decline in employment levels since mid-1980. We instead used a data set compiled by Young (2000). [We found the employment trends of this data set to be quite reasonable: for example, on overall average

annual growth rate of employment between 1978 and 1998 was 2.4.]

Physical capital is accumulated according to

$$K_{t+1} = I_t + (1-\delta)K_t,\ K_0 > 0,$$

where I_t and K_t denote investment and capital stocks, respectively, at time t; $\delta > 0$ represents the depreciation rate and K_0 is the initial capital stock. Thus, to compute capital stocks at time t we need investment data, depreciation rates, and estimates of initial capital stocks. We used investment data from the IMF database which was compiled from various issues of the provincial yearbook. This data set is available from 1952. However, we noted that the data were considerably low and volatile in the pre 1965 era. Furthermore, we found that the reported investment deflators very volatile and implausible.[19] As a result, we used GDP deflator to deflate investment series.[20] We assumed that the depreciation rate δ is 5 percent. We calculated initial capital stocks by $K_{65} = I_{65}/(g+\delta)$, where g is the annual growth rate of the capital stocks before 1965,[21] which we also assumed to be 5 percent. Finally, we obtained the foreign direct investment data from the IMF database.

B Kernel Estimator of a Distribution Function

A kernel estimator of a set of observations is an estimated distribution function from which the observations were likely driven. Specifically, a kernel-based estimator, $\tilde{f}(x)$, of a density

[19] For example, using these investment deflators we found that in some provinces in some years investment to GDP ratios were greater than 1.

[20] Even in this case we found some anomalies in the series. For example, investment to GDP ratio in Shanghai is on average less than 15 percent before 1980s. In that case, we assumed that the investment to output ratio between 1965-78 is the same with the average of the investment to output ratios of other provinces in the region. Similarly, we further noted that the investment data for Qinghai and Ningxia were relatively high over 1978-98. For example, their investment to GDP ratios were above 50 percent and in some years even reached 70 percent. Given that there are no significant changes in their output trends, we concluded that measurement errors could be one possible reason for these high investment levels. Consequently, we assumed that the investment to output ratio in each of these provinces is the same with the average of the investment to output ratios of other provinces in the region. These adjustments do not have any impact on either the position of frontier or the efficiency levels of other provinces. Without these adjustments, we estimated lower efficiency indexes for these provinces.

[21] Implicit in this formula is the assumption that the capital series has been growing at constant rate before the investment data became available. Young (1995) and Hall and Jones (1999) also used the same technique to estimate initial capital stocks.

function $f(x)$ of a random variable x is given by:

$$\tilde{f}(x) = \frac{1}{Nh} \sum_{i=1}^{N} \psi \left(\frac{x_i - x}{h} \right), \tag{11}$$

where $\int_{-\infty}^{\infty} \psi(s) ds = 1$ with $s = (x_i - x)/h$, and h is called optimal window width (or smoothing parameter). Here ψ is weighting function and in this paper, following Kumar and Russell (2002) and Aziz and Duenwald (2003), we assume that ψ is a standard normal density function. Following Silverman (1986), the optimal window width is chosen to be given by $h = 0.9AN^{-0.2}$, where $A = min\{$standard deviation, interquartile range/1.34$\}$. For more detail discussion on kernel estimators, see Silverman (1986).

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