

Since the start of economics reforms in 1978, China's growth record has been impressive, but the contribution of its provinces to per capita income growth has been highly uneven. (See, for example, Dayal-Gulati and Husain, 2002 and Aziz and Duenwald, 2003.) 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 on 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, Sachs, and Warner (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 does not hold. The absence of absolute convergence among China's provinces is in contrast with the behavior of U.S. 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 Sala-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 and others (2002) find that, after controlling for openness and proximity to fast-growing economies in East Asia, growth in coastal provinces benefits significantly from preferential policies, which have fostered marketization and internationalization. Dayal-Gulati and Husain (2002) show that the prevalence of state-owned enterprises 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 foreign direct investment (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 Solow 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 nonparametric technique known as Data Envelopment Analysis (DEA), pioneered by Farrell (1957) and Afriat (1972). 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 provincial 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.

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, whereas efficiency and technological improvements account for about 7 and 18 percent, respectively. The capital deepening is also the driving factor behind the changes in the *distributional dynamics* of the labor productivity over the past two decades. Second, technical change is not (Hicks) neutral. Third, while improvement in efficiency supports convergence in labor productivity between provinces, technical change contributes to productivity disparity across provinces. Finally, we find that FDI has a positive and significant effect on efficiency growth and technical progress.

This paper is related to a growing literature that develops a link between the DEA literature and the convergence literature. Key studies are Färe and others (1994), Kumar and Russell (2002), Henderson and Russell (2005), and Henderson, Tochkov, and Badunenko (2007). Färe and others were the first to use DEA to analyze the productivity growth in 17 OECD countries, and Kumar and Russell extend the work of Färe and others in a novel way to the tripartite decomposition to analyze the productivity performance across 57 countries. Henderson and Russell extend the Kumar and Russell analysis by incorporating human capital. Our approach is similar to that of Kumar and Russell, except that in constructing the production possibility frontier 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 undesirable feature in the findings of Kumar and Russell. Henderson and Russell also employ the method suggested by Diewert. However, owing to lack of data on human capital, they focus on two time periods, 1965 and 1990, and changes over this 25-year interval. Thus, in constructing the production frontier in 1990, they use only the base year and the final year data, which makes the frontier less precise.

The study most relevant to our work is Henderson, Tochkov, and Badunenko (2007).¹ They also use the Kumar and Russell (2002) decomposition to analyze provincial growth in China between 1978 and 2000. Their findings are similar to ours: (1) capital accumulation is the prime factor behind the growth performance of Chinese provinces, (2) technical change is not neutral, and (3) technical progress is responsible for disparity across provinces. In addition, they find that human capital is another important factor responsible for divergence across provinces.

However, there are differences between our paper and Henderson, Tochkov, and Badunenko (2007). When we investigate the relationship between the growth rates of the three components of labor productivity growth and the initial level of labor productivity, we also consider other possibly important factors (such as geography, and domestic and foreign investments). When we control for these additional factors, we find that there is support for conditional convergence in output per worker. More interestingly, we find that FDI has a positive and significant effect on efficiency growth and technical progress. On the other hand, Henderson, Tochkov, and Badunenko consider human capital accumulation, whereas we do not. But, incorporating human capital into their analysis does not come without concessions. Data on human capital are available for only three years; consequently, they construct their frontiers using only a few past observations as in Henderson and Russell (2005).²

I. A Glimpse of Productivity in China

Table 1 reports summary statistics for labor productivity between 1978 and 1998. Hainan and Tibet Autonomous Region were excluded for lack of data on value-added and fixed-capital investment. The sample is restricted to the period of 1978–98, owing to lack of comparable labor data for recent years. More detailed information about data sources and the construction of variables is provided in Appendix I.

¹We are indebted to an anonymous referee for bringing these studies to our attention, especially Henderson, Tochkov, and Badunenko (2007), which was independently written after this paper.

²Furthermore, in constructing human capital they assume that the rate of return to schooling is the same across all provinces and that this return is equal to the average rate of return to education from the Psacharopoulos (1994) world sample. We believe that rates of return to schooling are not the same across provinces and that the returns are different from the rates in Psacharopoulos.

Table 1. Descriptive Statistics for Labor Productivity, 1978–98

Province	Output per Worker (in yuan per worker)		Average Growth (in percent)
	Y ₁₉₇₈	Y ₁₉₉₈	g _y
Beijing	2,451	10,806	7.4
Tianjin	2,254	9,564	7.2
Hebei	868	4,049	7.7
Shanxi	912	3,392	6.6
Inner Mongolia	889	3,619	7.0
Liaoning	1,828	6,247	6.1
Jilin	1,270	4,213	6.0
Heilongjiang	1,736	4,404	4.7
Shanghai	3,907	19,367	8.0
Jiangsu	897	7,300	10.5
Zhejiang	689	5,906	10.7
Anhui	608	2,644	7.3
Fujian	718	5,358	10.0
Jiangxi	694	2,942	7.2
Shandong	759	3,864	8.1
Henan	580	2,618	7.5
Hubei	790	4,433	8.6
Hunan	645	2,292	6.3
Guangdong	817	6,402	10.3
Guangxi	521	1,974	6.7
Sichuan	580	2,323	6.9
Guizhou	442	1,474	6.0
Yunnan	526	1,981	6.6
Shaanxi	754	2,677	6.3
Gansu	933	2,248	4.4
Qinghai	1,074	2,397	4.0
Ningxia	959	2,849	5.4
Xinjiang	794	4,007	8.1
Mean	1,068	4,691	7.2
Std. Dev.	752	3,662	1.7

Sources: State Statistical Bureau; *China Statistical Yearbook*, various issues; and authors' calculations.

Note: This table reports labor productivity (output per worker) in 1978 and 1998 and its average annual growth rate between 1978 and 1998 for provinces in China.

It is interesting to look at the dynamics of productivity change across provinces. All provinces record increases in labor productivity between 1978 and 1998. 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 to 5 percent. In 1978, the coastal provinces are on average less productive than the landlocked provinces. In a ranking of provinces by level of labor productivity in 1978, with the most productive province at rank 1, Fujian, Guangdong, and Zhejiang rank 17th, 12th, and 16th, respectively, and 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: by 1998, Fujian, Guangdong, and Zhejiang rank 8th, 5th, and 7th, respectively, and 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 China as a whole.³

To provide a better understanding of the dynamics, in Figures 1a and 1b we plot the (kernel) distributions of productivity levels in 1978 and 1998.⁴ In both years, the distribution across provinces is multimodal.⁵ However, the shape of the distribution has changed over the past two decades. First, in both years, most provinces were clustered around a low productivity level. However, in 1998 the low productivity cluster had become considerably flatter, encapsulating the two intermediate clusters in the 1978 distribution. The result is a more bimodal distribution. Moreover, the mean of the low productivity cluster is higher in 1998, suggesting an increase in average productivity. Second, the peaks are farther apart in 1998 than in 1978, which suggests that although average output per worker has increased over our sample period, the distribution of income across provinces has become more uneven. Our purpose is to identify the factors that are responsible for this change in the overall distribution. But first, we need to introduce a basic framework to analyze this problem.

II. Basic Framework

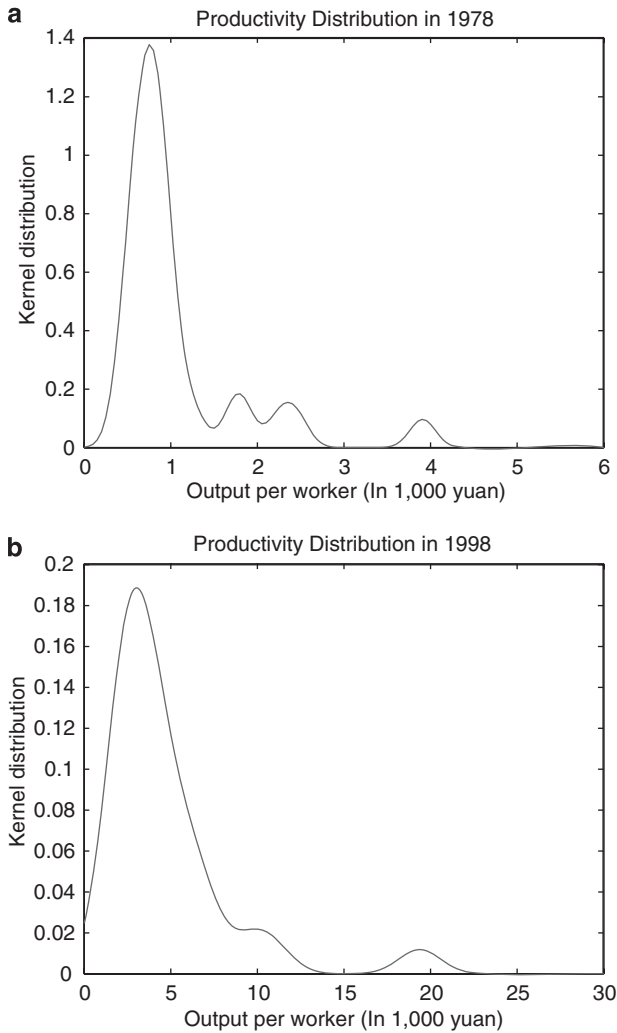
We begin by constructing production sets (and frontiers). As discussed in the Introduction, our approach to constructing production sets is data-driven. Roughly speaking, we define the production set at time t as the smallest convex set that envelops all available data at time t . The boundary of this set will represent the production frontier. Figure 2 illustrates how the frontier is constructed when there are three input-output combinations A , B , and C . In this figure, the single output, y , is produced from the single input, k , and the production frontier, $f(k)$, that characterizes the boundary of the production

³We 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.

⁴More information on the construction of kernel distributions is provided in Appendix II.

⁵This is in line with Aziz and Duenwald (2003) and Henderson, Tochkov, and Badunenko (2007).

Figure 1. Provincial Productivity Distribution in 1978 and 1998



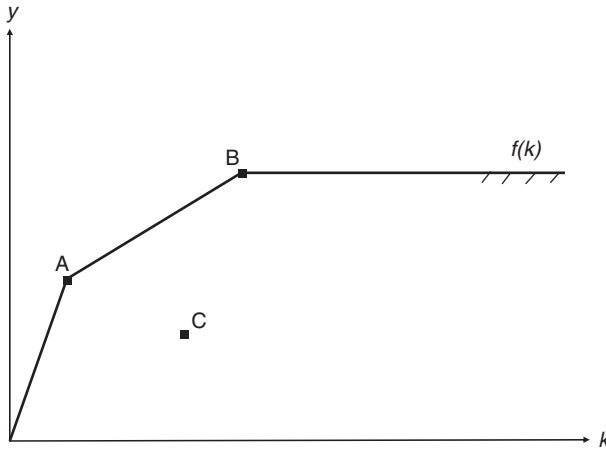
Sources: State Statistical Bureau; *China Statistical Yearbook*, various issues; and authors' calculations.

Note: These figures plot the distributions of labor productivity (output per worker) levels in 1978 and 1998. These estimated (kernel) distributions are constructed from observed data.

set exhibits nonincreasing returns to scale. Points *A* and *B* are on the frontier, whereas point *C* is in the interior of the production set (hence, it is inefficient).

More formally, we construct the production frontier as follows. Let $f_t(\cdot)$ be a nonincreasing returns to scale (NIRS) production function that gives the maximum amount $f_t(k_t)$ of output per worker that can be produced using k_t

Figure 2. Construction of Production Set



Note: This figure illustrates how the frontier is constructed when there are three input-output combinations: A , B , and C . In this figure, the single output, y , is produced from the single input, k , and the production frontier, $f(k)$, is the boundary of the smallest convex set that envelops all available data.

amount of capital per worker.⁶ Then, the production set is constructed from the data as follows.

$$\mathcal{P}_t = \left\{ (k_t, y_t)' \in \mathbb{R}_+^2 : y_t \leq \sum_{\tau \leq t} \sum_i \theta_\tau^i y_\tau^i, \sum_{\tau \leq t} \sum_i \theta_\tau^i k_\tau^i \leq k_t, \theta_\tau^i \geq 0, \right. \\ \left. \text{and } \sum_{\tau \leq t} \sum_i \theta_\tau^i \leq 1 \right\}, \quad (1)$$

where θ_τ^i represents “weights” and $(k_\tau^i, y_\tau^i)'$ 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.⁷ By imposing the restriction $\sum_{\tau=1}^t \sum_{i=1}^I \theta_\tau^i \leq 1$, we make the production technology exhibit NIRS (Afriat, 1972). Note that this production technology also

⁶In fact, we have two inputs, capital, K , and labor, L , and the single output Y . The production frontier is characterized by a *constant returns to scale* (CRS) production function F_t . Because F is a CRS production function, $Y_t = F_t(K_t, L_t)$ can be written as $y_t = f_t(k_t)$, where $k_t = K_t/L_t$ and $y_t = Y_t/L_t$. Note that in this case, $f_t(\cdot)$ exhibits nonincreasing returns to scale.

⁷For excellent discussions of the construction of production frontiers and DEA, see Farrell (1957), Afriat (1972), and Färe, Grosskopf, and Lovell (1994). In particular, Färe, Grosskopf, and Lovell give a comprehensive account of various extensions of DEA.

satisfies the free-disposal condition that 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 and others (1994), who construct the frontier by using only the input-output data observed at time t . We incorporated previous observations to prevent the possibility of an implosion of the technological frontier over time.⁸

For a given point (k_t, y_t) in the production set, we define the output-based (or Farrell) efficiency function as follows:

$$E_t(k_t, y_t) = \min\{\lambda : (k_t, y_t/\lambda)' \in \mathcal{P}_t\}. \quad (2)$$

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 , the efficiency index λ_t^i at time t is then calculated by solving a linear programming (LP) problem based on Equation (2) (see Färe, Grosskopf, and Lovell, 1994). Having calculated the efficiency indices, we can decompose productivity growth into efficiency, technological change, and capital deepening components, as in Kumar and Russell (2002).

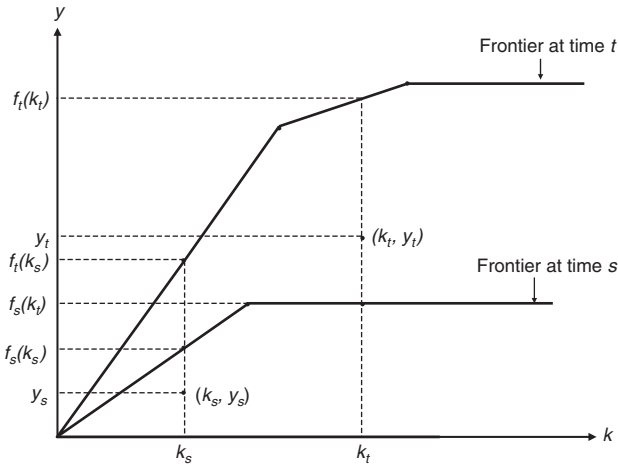
To illustrate the decomposition of output per worker, Figure 3 depicts two production sets for time periods s and t , with $s < t$. Points (k_s, y_s) and (k_t, y_t) represent the input-output combinations of the same economy in periods s and t , respectively. Note that these observed input-output combinations 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

$$\frac{y_t}{y_s} = \frac{\lambda_t \times f_t(k_t)}{\lambda_s \times f_s(k_s)}. \quad (3)$$

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

⁸Nothing 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 , that does not include all the elements in the production set at date $s < t$.

Figure 3. Decomposition of Output per Worker



Note: This figure 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. These observations are in the interiors of the corresponding production sets, and hence, inefficient. The efficiency index for (k_s, y_s) at time s is given by $y_s/f(k_s)$, and the efficiency index for (k_t, y_t) at time t is given by $y_t/f(k_t)$.

terms we obtain

$$\frac{y_t}{y_s} = \frac{\lambda_t}{\lambda_s} \times \frac{f_t(k_t)}{f_s(k_t)} \times \frac{f_s(k_t)}{f_s(k_s)}. \tag{4}$$

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 the efficiency index over these two periods. The second term represents the shift in the production frontier at capital intensity 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 (4) decomposes labor productivity into three components: change in the efficiency index, change in technology, and change in capital intensity. Note that this is not the only way to decompose output per worker. Considering again Equation (3), multiplying the numerator and denominator on the right-hand side by $f_s(k_s)$, which is the maximum output that can be produced with input level k_s under the second-period production technology, and rearranging terms we get

$$\frac{y_t}{y_s} = \frac{\lambda_t}{\lambda_s} \times \frac{f_t(k_s)}{f_s(k_s)} \times \frac{f_t(k_t)}{f_t(k_s)}, \tag{5}$$

where each term on the right-hand side is interpreted in the same way as in Equation (4). Note that unless the production technology F is Hicks-neutral, there is no reason to expect that $f_t(k_s)/f_s(k_s)$ equals $f_t(k_t)/f_s(k_t)$. Hence, we

have two different representations of technical change (and of the change in potential output owing to the change in capital intensity, which is the third term in Equations (4) and (5)). Following Färe and others (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 Equations (4) and (5):

$$\frac{y_t}{y_s} = \frac{\lambda_t}{\lambda_s} \times \left(\frac{f_t(k_t) f_t(k_s)}{f_s(k_t) f_s(k_s)} \right)^{1/2} \times \left(\frac{f_s(k_t) f_t(k_t)}{f_s(k_s) f_t(k_s)} \right)^{1/2} \quad (6)$$

Taking the logarithms of both sides of Equation (6) and dividing by $t-s$ (number of years between two periods), we have

$$g_y = g_{eff} + g_{tech} + g_{cap}, \quad (7)$$

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 the 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. We use identity (7) in reporting our results, and this presentation is different from that in Kumar and Russell (2002), who use identity (6). Our approach seems more appealing than that based on Equation (6), because in this way we present the average annual growth rate of output per worker as the *sum* of the average annual growth rates of the efficiency index, technical progress, and capital per worker between two periods.

This completes the theoretical framework of our approach. 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 efficiency indices. Finally, we illustrated how, after having calculated the efficiency indices, growth in output per worker can be decomposed into changes in efficiency, technology, and capital intensity.

At this stage, it is important to highlight the important features of this approach and compare this approach with the standard accounting approach. First, the two approaches are conceptually different and this difference comes from the construction of the production frontier and the positions of economies relative to the frontier. Under the nonparametric approach, we construct a countrywide production frontier with most provinces staying below the frontier; in the standard accounting approach, each province is assumed to be on its own frontier and each province's performance is compared only with its previous-year performance, not with a common benchmark across all provinces. Because we want to compare the relative performance of the provinces, we think that our nonparametric approach is more suitable.

Second, in the standard accounting approach, it is assumed that all observations share a *common* production function with different shift

parameters called the Solow Residual (or total factor productivity, TFP). More formally, it is usually assumed that the production function is given by $Y_t = A_t F(K_t, L_t)$, where A represents TFP and F is a CRS function. This can further be written in intensive form as $y = A_t f(k_t)$. Consider two observations at dates s and t ; then we have

$$\frac{y_t}{y_s} = \frac{A_t f(k_t)}{A_s f(k_s)}. \tag{8}$$

Thus, we can decompose the change in output per worker into two components: change in TFP and change in capital-labor ratio. As also noted by Henderson and Russell (2005), a comparison of the right-hand sides of Equations (6) and (8) suggests that the first two components in Equation (6) are *roughly* encapsulated by the TFP ratio in Equation (8). Thus, our approach allows for the separation of changes in efficiency from technological progress. Decomposing the change in TFP into finer components and investigating their contributions to labor productivity is another important reason for us to use this nonparametric technique.⁹

Third, our nonparametric approach does not impose any kind of structure on markets as the standard accounting approach does. To see this, note that taking the logarithm of both sides in Equation (8), differentiating with respect to time, and rearranging the terms yields

$$g_{Y/L} = g_A + (1 - \varepsilon_L)g_{K/L},$$

where ε_L is the elasticity of labor with respect to output and g_X denotes the growth rate of the variable X . In practice, we do not know the elasticity ε_L . To overcome this difficulty, it is assumed that markets are competitive, which implies that the labor elasticity can be replaced with the share of 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

⁹Hall and Jones (1999) advocate a different decomposition than Equation (8). They assume that the production function is Cobb-Douglas, $Y = K^{1-\alpha}(AL)^\alpha$, and rewrite it as $y \equiv Y/L = A(K/Y)^{(1-\alpha)/\alpha}$. (Notice that here A equals $A^{1/(1-\alpha)}$ in Equation (8).) This presentation is more insightful than the standard approach in Equation (8), because it assigns the long-run effects of changes in capital and TFP entirely to those variables. Consider two observations at dates s and t , then their decomposition yields:

$$\frac{y_t}{y_s} = \frac{A_t}{A_s} \left(\frac{K_t/Y_t}{K_s/Y_s} \right)^{\frac{1-\alpha}{\alpha}}.$$

This decomposition is not really comparable to our decomposition in Equation (6), because it contains the capital-output ratio rather than the capital-labor ratio as a measure of capital deepening. However, when we use this decomposition to analyze change in output per worker between 1978 and 1998 in each province, we find that the contribution from the capital-output ratio to output per worker is relatively small (usually less than 20 percent; the results are available upon request). Because the contribution to labor productivity growth from the change in the capital-output ratio is relatively small, a comparison of Equation (6) and the Hall and Jones decomposition implies that the TFP in the Hall and Jones decomposition *very roughly* encompasses all three components of Equation (6).

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 above accounting framework.¹⁰

Finally, in the standard accounting approach, calculation of TFP *levels* requires certain restrictions on the production function. Klenow and Rodríguez-Clare (1997) and Hall and Jones (1999), for example, assume that the production function is Cobb-Douglas, which further implies that technological progress is Hicks-neutral. In our analysis, we do not impose any restriction (other than the CRS assumption) on the shape of the production function, and hence, no restriction on the type of technical change. Indeed, our analysis in the next section suggests that technological progress is not Hicks-neutral.

These appealing features do not come without some limitations. 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 indices represent lower bounds of the true inefficiencies. Second, our approach is deterministic and it does not take into account possible measurement errors. These measurement errors can change the shape of the frontier, which can further affect each component of the tripartite decomposition. In this case, the direction of bias in each component can go either way. There is an alternative technique, known as the stochastic frontier approach, to calculate the efficiency indices under possible measurement errors. We did not consider this approach in our study because its implementation imposes additional restrictions on the functional form of the frontier and error terms.

III. Results

Table 2 reports summary statistics for efficiency.¹¹ We note that Heilongjiang, Jiangsu, and Shanghai have efficiency indices of 1 in 1978.¹² This result implies that 25 provinces are below the technology frontier. Figure 4a illustrates the positions of the provinces relative to the technology

¹⁰We 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 (2003). It is clear from the above equation that using small labor shares would exaggerate the contribution of the capital-labor ratio to labor productivity growth.

¹¹These results differ somewhat from those in Unel and Zebregs (2006), because here capital stocks are constructed using longer investment series, which makes estimates more reliable (see Appendix I).

¹²The efficiency indices are calculated by solving the corresponding linear programming problem 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).

frontier in 1978 and suggests considerable dispersion of production activities.¹³

The second column of Table 2 reports the efficiency indices in 1998. In that year, only Shanghai has an efficiency index of 1.¹⁴ Figure 4b 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, and 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. We note that, compared with Figure 4a, 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 (see also the last column of Table 2). These trends suggest convergence in both the mean and the standard deviation of efficiency indices across provinces over 1978–98.¹⁵ There are two important points to notice in this figure. First, because the input-output combinations of Anhui in 1984, Fujian in 1994, and Shanghai in 1985 and 1997 are on the 1998 frontier, excluding the intermediate years in constructing the frontier, as in Henderson and Russell (2005) and Henderson, Tochkov, and Badunenko (2007), would significantly change the shape of the frontier. Second, 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 suggests that the technical progress has not been Hicks-neutral.

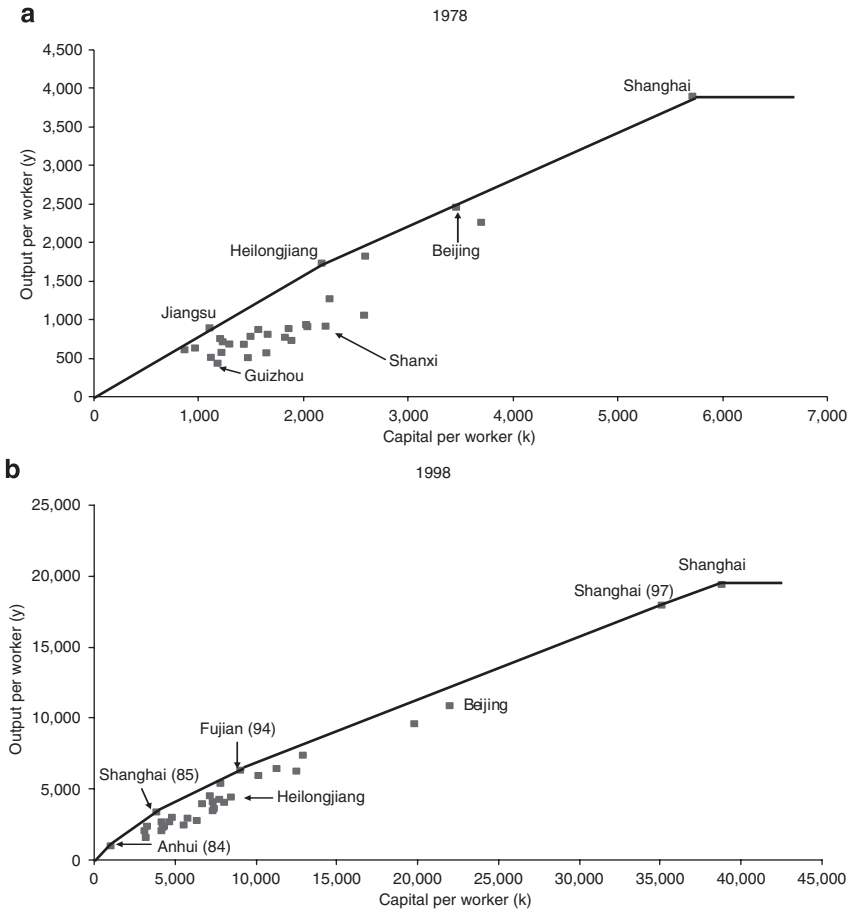
To determine which factor has played the most significant role in provincial growth dynamics, we now turn to the decomposition of labor productivity into capital deepening, efficiency gains, and technological progress. Table 3 shows the results of this decomposition and the relative contributions of the three factors to productivity growth between 1978 and 1998. Note that average productivity growth is 7.2 percent, of which 5.4 percentage points are accounted for 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

¹³Our findings are different from those in Henderson, Tochkov, and Badunenko (2007). They find that only Shanghai is on the frontier. However, this stems from their frontier construction in which they also consider human capital. Hence, $k = K/H$ and $y = Y/H$, where H is the total human capital, in their (k, y) space presentation.

¹⁴We 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.

¹⁵Similar to the labor productivity case, to test for absolute convergence in efficiency across provinces we run the regression $g_{\lambda}^i = \beta_0 + \beta_1 \ln(\lambda_{1978}^i) + \varepsilon$, where g_{λ}^i 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 indices.

Figure 4. Production Sets and Frontiers in 1978 and 1998



Sources: State Statistical Bureau; *China Statistical Yearbook*, various issues; *The Gross Domestic Product of China, 1952–95*; and authors' calculations.

Note: These figures represent production sets and their frontiers in 1978 and 1998, respectively. Output per worker, y , is produced with capital per worker, k , and the production frontier is the boundary of the smallest convex set that envelops all available data. Any observed input-output combination below a frontier is inefficient.

for about 18 and 7 percent, 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 and Li, 1999; and Heytens and Zebregs,

¹⁶This conclusion remains broadly the same for subperiods. 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 percent, respectively. These results are available from the authors upon request.

Table 2. Descriptive Statistics for Efficiency, 1978–98

Province	Efficiency Levels		Average Growth (in percent)
	λ_{1978}	λ_{1998}	g_{λ}
Beijing	0.969	0.894	-0.4
Tianjin	0.843	0.859	0.1
Hebei	0.687	0.759	0.5
Shanxi	0.517	0.637	1.0
Inner Mongolia	0.594	0.671	0.6
Liaoning	0.918	0.794	-0.7
Jilin	0.710	0.758	0.3
Heilongjiang	1.000	0.732	-1.6
Shanghai	1.000	1.000	0.0
Jiangsu	1.000	0.906	-0.5
Zhejiang	0.658	0.865	1.4
Anhui	0.859	0.754	-0.7
Fujian	0.723	0.949	1.4
Jiangxi	0.601	0.761	1.2
Shandong	0.778	0.782	0.0
Henan	0.585	0.694	0.9
Hubei	0.654	0.846	1.3
Hunan	0.826	0.804	-0.1
Guangdong	0.611	0.871	1.8
Guangxi	0.576	0.723	1.1
Sichuan	0.437	0.645	1.9
Guizhou	0.460	0.534	0.7
Yunnan	0.443	0.563	1.2
Shaanxi	0.500	0.559	0.6
Gansu	0.573	0.631	0.5
Qinghai	0.541	0.558	0.2
Ningxia	0.590	0.641	0.4
Xinjiang	0.541	0.697	1.3
Mean	0.686	0.746	0.5
Std. Dev.	0.178	0.127	0.8

Sources: State Statistical Bureau; *China Statistical Yearbook*, various issues; *The Gross Domestic Product of China*, 1952–95; and authors' calculations.

Note: This table reports efficiency indices in 1978 and 1998, and their average annual growth rate between 1978 and 1998 for provinces in China. The efficiency index is calculated as a relative distance to the production frontier constructed in (k, y) space.

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

Table 3. Decomposition of Labor Productivity Growth, 1978–98
(In percent)

Province	Productivity Growth g_y	Change in Efficiency g_{eff}	Change in Technology g_{tech}	Capital Deepening g_{cap}	Relative Contribution of		
					Efficiency	Technology	Capital
Beijing	7.4	-0.4	3.2	4.6	-5.4	43.5	61.9
Tianjin	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
Jilin	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
Guangxi	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
Xinjiang	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: State Statistical Bureau; *China Statistical Yearbook*, various issues; *The Gross Domestic Product of China, 1952–95*; and authors' calculations.

Note: This table shows the decomposition of labor productivity (output per worker) growth, g_y , into change in efficiency, g_{eff} , change in technology, g_{tech} , and capital deepening, g_{cap} , so that $g_y = g_{eff} + g_{tech} + g_{cap}$. The last three columns show the relative contributions of these components to productivity growth between 1978 and 1998. Change in efficiency represents movements toward or away from the production frontier over time; technical change measures a shift of the production frontier; and capital deepening represents change in maximum output per worker owing to a change in capital intensity between the two periods.

Heilongjiang, Anhui, Hunan, and Shandong during 1978–98 is at least 90 percent, whereas it is less than 65 percent in Beijing, Tianjin, Sichuan, and Shanghai. We also see that while technical progress has been an important driver of productivity growth in Beijing, Tianjin, Liaoning, Heilongjiang, and

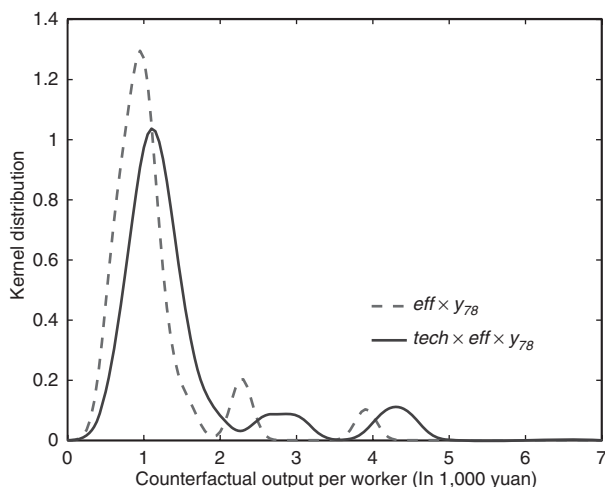
(in particular) Shanghai, it was not as important as improvements in efficiency in Jiangxi, Guangxi, Sichuan, and Yunnan.

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, that is, $y_E \equiv (\lambda_{98}/\lambda_{78}) \times y_{78}$. The kernel distribution of y_E is shown by the dashed line in Figure 5; notice that this transformation changes the initial shape of the labor productivity distribution a little compared to Figure 1a, but dispersion between the poorer mode and the richer ones remains almost the same. To see the effect of technical progress, we further multiply y_E by the second term in Equation (6). This effect is illustrated by the solid line in Figure 5. This operation has shifted the distribution slightly to the right and made the middle mode thicker, but the overall shape and dispersion among modes remain mostly unchanged. This analysis shows that capital deepening is also the driving factor for changes in the *distributional* dynamics of labor productivity. Indeed, if we multiply the second distribution by the last term (that is, capital deepening) in Equation (6), we obtain Figure 1b.

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 regress the average annual growth rate of each variable on initial labor productivity along with other variables such as FDI, domestic investment, and geography. Our regressions are different from those in Kumar and Russell (2002) and Henderson, Tochkov, and Badunenko (2007), who only consider the initial level of labor productivity as a regressor. We also consider other factors, because they might have possible effects on the growth rates of the three components.¹⁷ For example, the existence of foreign firms may foster competition among domestic firms, which in turn may increase their efficiency. Moreover, foreign firms may help technical progress by

¹⁷One may worry that if these variables can affect efficiency, why are they not included in the production function described in Section I? We must point out that FDI is indeed included in the production function, because the capital stock is constructed from investment data that are the sum of domestic and foreign investment series. The geographical setting, on the other hand, is not included, simply because we do not know how to incorporate the geographical settings into the production function. One possible approach is to divide the sample into two, and construct one production frontier for the coastal provinces, and another for inland provinces; then, we can calculate efficiency indices with respect to each production frontier. This approach, however, is not satisfactory for two reasons. First, each frontier would be constructed using fewer data points, which makes estimates less precise. Second, we want to compare the relative performance of *all* provinces with respect to a benchmark, and we can achieve this only by constructing a countrywide production frontier.

Figure 5. Counterfactual Productivity Distributions in 1998



Source: Authors' calculations.

Note: This figure shows the effects of changes in efficiency and technology on the distributional dynamics of labor productivity (output per worker). The dashed line represents the distribution of output per worker when only the change in the efficiency index over 1978–98 is considered, that is, change in efficiency $\times y_{78}$; where y_{78} is output per worker in 1978. The solid line, on the other hand, represents the combined effects of changes in efficiency and technology, that is, change in technology \times change in efficiency $\times y_{78}$.

bringing new technologies to the country. The regression results are presented in Table 4.¹⁸

Column 1 in Table 4 represents results where the dependent variable is labor productivity. Here the coastal dummy is significant at the 10 percent level, whereas the FDI-GDP ratio and the initial productivity level are significant at the 5 percent level. The negative and significant coefficient on initial labor productivity 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 the efficiency index. The coefficient on 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. This together with decomposition (8) implies that improvements in efficiency support convergence across provinces. We also see that FDI had a positive and significant effect on efficiency growth.

¹⁸The 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 an instrumental variables approach. Unfortunately, there is no good instrument to control for this reverse effect.

Table 4. Regression Results

	Dependent Variable			
	g_y (1)	g_{eff} (2)	g_{tech} (3)	g_{cap} (4)
FDI/GDP	0.380* (0.123)	0.161* (0.046)	0.106** (0.055)	0.116 (0.086)
Inv/GDP	-0.016 (0.075)	0.068 (0.046)	0.012 (0.021)	-0.098 (0.059)
Coastal dummy	0.014** (0.08)	-0.002 (0.004)	0.004 (0.002)	0.012** (0.007)
$\ln y_{78}$	-0.011* (0.004)	-0.011* (0.003)	0.013* (0.002)	-0.013* (0.004)
Adjusted R^2	0.435	0.363	0.786	0.354

Note: This table shows the results of regressions in which the average annual growth rate of each variable is regressed on foreign direct investment, domestic investment, a geography dummy, and initial labor productivity. The dependent variables in columns (1)–(4) are the average annual growth rates of output per worker, efficiency, technology, and capital deepening, respectively. There are 28 observations, and numbers in parentheses represent robust standard errors. All regressions include an unreported constant term; *(**) means the corresponding coefficient is significant at the 5 (10) percent level.

When we regress changes in technology on the initial productivity level and other control variables, we find that the coefficient on initial productivity is positive and statistically significant (see Table 4, column 3). This suggests that there has been more technical progress in the initially more productive provinces than the less productive provinces. Combined with Equation (8), this further implies that technical change contributes to productivity disparity across provinces. This result supports 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 (see, for example, Nelson and Phelps, 1966, and Findlay, 1978). Note that the coefficient of FDI is positive and statistically significant.

The positive and significant effects of FDI on efficiency and technical change reflect increased competition, better management of resources, marketing channels, and new technologies brought by FDI. For example, the technology transfer to production facilities in China by foreign multinationals is now larger than all other forms of domestic technology development (Naughton, 2007). FDI has also played an extremely important role in China's rapid expansion in world trade. It has, for example, forced an increasing number of domestic manufacturers to compete globally, which has further integrated China into global production (Chen, Chang, and Zhang, 1995).

Finally, column 4 in Table 4 represents results when the dependent variable is the growth rate of capital deepening. The negative and significant coefficient on initial labor productivity suggests that capital deepening was higher in initially less developed provinces.¹⁹ Surprisingly, neither FDI nor domestic investment had any significant effects on the growth rate of capital deepening.

IV. Conclusion

We have used a nonparametric approach to decompose labor productivity growth in China's provinces into three components: efficiency gains, technological progress, and capital deepening. This decomposition has allowed us to investigate the contribution of each of the three factors to 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. Moreover, capital deepening is the prime factor for the change in the dynamics of labor productivity. Whereas improvement in efficiency contributes to convergence in labor productivity between provinces, technical change contributes to productivity disparity across provinces. Finally, we find that FDI has a positive and significant effect on efficiency growth and technical progress.

Improvements in efficiency between 1978 and 1998—especially in the initially least productive provinces, which often had the largest agricultural sectors—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 nonstate sector. Positive effects of FDI on efficiency gains and technical change, on the other hand, reflect competition, technology transfers, and a more efficient allocation of resources associated with large FDI inflows.

APPENDIX I

Data

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 *China Statistical Yearbook*.

Labor data reported in the *China Statistical Yearbook* contain large swings and do not take into account the possible changes in employment due to migration between provinces. For example, according to the reported series there was a substantial decline in employment levels from the mid-1980's onward. We instead used a data set compiled by

¹⁹The effects of the initial productivity level on the growth rates of the three components are in line with Kumar and Russell (2002) and Henderson, Tochkov, and Badunenko (2007). Although there is no absolute convergence in labor productivity as in their results, we find that after controlling for other factors there is convergence in labor productivity across provinces.

Young (2000). We found the employment trends of this data set to be quite reasonable: for example, the overall average annual growth rate of employment between 1978 and 1998 was 2.4 percent.

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 compiled investment data from *The Gross Domestic Product of China, 1952–95*. Unfortunately, the observations before 1965 seem problematic because they show greater variation and are considerably lower than observations from the post-1965 period. Furthermore, we found that the reported investment deflators were very volatile and implausible.²⁰ As a result, we used the GDP deflator to deflate the investment series.²¹ 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 1965,²² which we also assumed to be 5 percent. Finally, we constructed the FDI series with data from the *China Statistical Yearbook*.

APPENDIX II

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 drawn. Specifically, a kernel-based estimator $\tilde{f}(x)$, of a density function $f(x)$ of a random variable x is given by

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

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 a weighting function and in this paper, following Kumar

²⁰For example, using these investment deflators we found that in some provinces in some years investment-to-GDP ratios were greater than 1.

²¹Even in this case we found some anomalies in the series. For example, the investment-GDP ratio in Shanghai is on average less than 15 percent before the 1980s. In that case, we assumed that the investment-output ratio between 1965 and 1978 is the same as the average of the investment-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-output ratio in each of these provinces is the same as the average of the investment-output ratios of other provinces in the region. These adjustments do not have any impact on either the position of the frontier or the efficiency levels of other provinces. Without these adjustments, we estimated lower efficiency indices for these provinces.

²²Implicit in this formula is the assumption that the capital series had been growing at a 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.

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 $h=0.9 AN^{-0.2}$, where $A = \min\{\text{standard deviation, interquartile range}/1.34\}$. For a more detailed discussion on kernel estimators, see Silverman (1986).

REFERENCES

- Afriat, Sydney, 1972, "Efficiency Estimation of Production Functions," *International Economic Review*, Vol. 13 (October), pp. 568–98.
- Aziz, Jahangir, and Christoph Duenwald, 2003, "Provincial Growth Dynamics," in *China: Competing in the Global Economy*, ed. by Wanda Tseng and Markus Rodlauer (Washington, International Monetary Fund).
- Barro, Robert J., and Xavier Sala-i-Martin, 2004, *Economic Growth* (Cambridge, Massachusetts, MIT Press, 2nd ed.).
- Bell, Michael W., Hoe Ee Khor, and Kalpana Kochhar, 1993, *China at the Threshold of a Market Economy*, IMF Occasional Paper No. 107 (Washington, International Monetary Fund).
- Chen, C., L. Chang, and Y. Zang, 1995, "The Role of Foreign Direct Investment in China's Post-1978 Economic Development," *World Development*, Vol. 23 (April), pp. 691–703.
- Chow, Gregory C., and Kui-Wai Li, 1999, "Accounting for China's Economic Growth: 1952–1998" (unpublished; Princeton, New Jersey, Princeton University). Available via the Internet: www.princeton.edu/erp/papers/chow2.pdf.
- Dayal-Gulati, Anuradha, and Aasim M. Husain, 2002, "Centripetal Forces in China's Economic Take Off," *IMF Staff Papers*, Vol. 49 (September), pp. 364–94.
- Démurger, Sylvie, Jeffrey D. Sachs, Wing Thye Woo, Shuming Bao, and Gene Chang, 2002, "The Relative Contributions of Locational and Preferential Policies in China's Regional Development: Being in the Right Place and Having the Right Incentives," *China Economic Review*, Vol. 13 (December), pp. 444–65.
- Diewert, W.E., 1980, "Capital and the Theory of Productivity Measurement," *American Economic Review, Papers and Proceedings*, Vol. 70 (May), pp. 260–7.
- Färe, Rolf, Shawna Grosskopf, and C.A. Knox Lovell, 1994, *Production Frontiers* (Cambridge, United Kingdom, Cambridge University Press).
- , Mary Norris, and Zhongyang Zhang, 1994, "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries," *American Economic Review*, Vol. 84 (March), pp. 66–83.
- Farrell, Michael J., 1957, "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society*, Vol. 120, No. 3, pp. 253–90.
- Findlay, Ronald E., 1978, "Relative Backwardness, Direct Foreign Investment, and the Transfer of Technology: A Simple Dynamic Model," *Quarterly Journal of Economics*, Vol. 92 (February), pp. 1–16.
- Hall, Robert E., and Charles I. Jones, 1999, "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" *Quarterly Journal of Economics*, Vol. 114 (February), pp. 83–16.
- Henderson, Daniel J., and R. Robert Russell, 2005, "Human Capital and Convergence: A Production Frontier Approach," *International Economic Review*, Vol. 46 (November), pp. 1167–205.

- , Kiril Tochkov, and Oleg Badunenko, 2007, “A Drive up the Capital Coast? Contributions to Post-Reform Growth Across Chinese Provinces,” *Journal of Macroeconomics Economics*, Vol. 29 (September), pp. 569–94.
- Heytens, Paul, and Harm Zebregs, 2003, “How Fast Can China Grow?” in *China: Competing in the Global Economy*, ed. by Wanda Tseng and Markus Rodlauer (Washington, International Monetary Fund).
- Jian, Tianlum, Jeffrey D. Sachs, and Andrew M. Warner, 1996, “Trends in Regional Inequality in China,” NBER Working Paper No. 5412 (Cambridge, Massachusetts, National Bureau of Economic Research).
- Klenow, Peter, and Andrés Rodríguez-Clare, 1997, “The Neoclassical Revival in Growth Economics: Has It Gone Too Far?” in *NBER Macroeconomics Annual*, ed. by Ben S. Bernanke and Julio J. Rotemberg (Cambridge, Massachusetts, MIT Press).
- Kumar, Subodh, and R. Robert Russell, 2002, “Technological Change, Technological Catch-up, and Capital Deepening: Relative Contributions to Growth and Convergence,” *American Economic Review*, Vol. 92 (June), pp. 527–47.
- Naughton, Barry, 2007, *The Chinese Economy, Transitions and Growth* (Cambridge, Massachusetts, MIT Press).
- Nelson, Richard R., and Edmund S. Phelps, 1966, “Investment in Humans, Technological Diffusion, and Economic Growth,” *American Economic Review*, Vol. 56 (March–May), pp. 69–75.
- Psacharopoulos, G., 1994, “Returns to Investment in Education: A Global Update,” *World Development*, Vol. 22 (September), pp. 1325–43.
- Silverman, Bernard W., 1986, *Density Estimation for Statistics and Data Analysis* (New York, Chapman & Hall).
- Unel, Bulent, and Harm Zebregs, 2006, “The Dynamics of Provincial Growth in China: A Nonparametric Approach,” IMF Working Paper 06/55 (Washington, International Monetary Fund).
- Young, Alwyn, 1995, “The Tyranny of Numbers: Confronting the Statistical Realities of the East Asian Growth Experience,” *Quarterly Journal of Economics*, Vol. 110 (August), pp. 641–80.
- , 2000, “The Razor’s Edge: Distortions and Incremental Reform in the People’s Republic of China,” *Quarterly Journal of Economics*, Vol. 115 (November), pp. 1091–135.
- , 2003, “Gold into Base Metals: Productivity Growth in the People’s Republic of China During the Reform Period,” *Journal of Political Economy*, Vol. 111 (December), pp. 1220–61.
- Zebregs, Harm, 2003, “Foreign Direct Investment and Output Growth,” in *China: Competing in the Global Economy*, ed. by Wanda Tseng and Markus Rodlauer (Washington, International Monetary Fund).