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2010

China Economic Review, 22 (3) September, 2011: 357-372

An Analysis on Technical Efficiency in Post-reform China

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Abstract:

This paper employs a fully nonparametric stochastic frontier model with time and individual effects to study technical efficiency in China's post-reform economy. The panel data cover China's thirty provinces for the period of 1985-2008. The empirical results show that the average output elasticity of labor is larger than the other two inputs of capital and human capital. Based on the specified inefficiency Tobit model, the factor analysis on technical efficiency shows that the time effects of technical efficiency in China's post-reform economy are significantly contingent on the factors. There exists significant regional differences in technical efficiency in China's economic development, and a number of policy implications can be drawn.

Key words: Fully nonparametric stochastic frontier; time effects and individual effects; time variant; technical efficiency; Tobit model.

JEL Classifications: C52, D24, O47

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Acknowledgement: The authors are indebted to the invaluable comments from the referees and would like to express their gratitude for the various research funding supports. Zhou's research was supported by the National Natural Science Foundation of China (Grant 70971143), and Li's research funding was supported by the City University of Hong Kong under two Strategic Research Grants (Numbers 7001907 and 7002175). Research assistance from Liang Wang, Helen H. K. Lam, Pang Yu and Lan Ting are gratefully acknowledged. The usual disclaimer applies.

1. Introduction

The discussion on the sustainability of economic growth in China's post-reform economy has led to studies on China's productivity, using either growth accounting or stochastic frontier analysis (SFA) (Chen *et al.*, 2009; Chen *et al.*, 2008; Wu, 2000, 2003, 2004; Hu and Khan, 1997; Woo, 1998; Mao and Koo, 1997; Borenstein and Ostry, 1996; Yang and Lahr, 2010). For example, the studies by Chow and Li (2002) and Li (2003) used investment figures to construct capital stock to estimate China's national total factor productivity (TFP) growth rates have been extended by Liu and Li (2006) and Li (2009) who incorporated the human capital variable and alternative investment data to examine both national and provincial TFP growth rates. Similar studies by Wang and Yao (2003) have examined the sources of China's economic growth, while Swamy (2003), Motohashi (2007) and Bosworth and Collins (2008) have compared China's TFP with other world economies.

In studying the technical change in the United States, Solow (1957) differentiated the movement along the production function caused by input growth from shift in the production function caused by technical progress. Both Bauer (1990) and Kumbhakar and Lovell (2000) have shown that TFP growth composes of technical progress, technical efficiency change and a scale economies effect. In theory, technical progress is an outward shift of the production frontier and technical efficiency change shows the movement from a position within towards a position on the production frontier, while the scale economies effect reflects an increase in return to scale.

Other studies have elaborated and extended China's post-reform economic productivity to efficiency analysis by using the Malmquist productivity index (MPI) and data envelop analysis (DEA) (Wu, 1995, 2008). The MPI that decomposes productivity into efficiency and technological change has also been applied in Ma *et al*. (2002) and Movshuk (2004). Studies on the productivity and efficiency performance of individual industries in China have been conducted by Jefferson (1990) and Mu and Lee (2005), while Yao *et al*. (2007) and Sun *et al*. (1999) agreed that SFA and DEA are the more effective approach to measure the technical efficiency of industries. The SFA used in studies on the China's economy have provided useful implications on the production function and technical efficiency performance (Huang and Kalirajan, 1998; Kalirajan *et al.*, 1996; Brummer *et al.,* 2006; Hu and McAleer, 2005; Tong, 1999; Wu 2000, 2003; Fu, 2005).

Nonetheless, studies on China's post-reform economy have provided a continued debate on whether technical progress or technical efficiency is the more important contributing factor to China's TFP growth (Wu, 2000; Li and Liu, 2011). After more than three decades of economic reform since 1978, it would be useful to examine if technical efficiency has become an important factor in China's growth. In addition, an objective measure on the technical efficiency among China's provinces is crucial. Given the extraordinary nature, the heterogeneity of development in various regions and different time periods, a flexible stochastic frontier model can be used to study technical efficiency in the post-reform China's economy.

Empirical studies using the conventional stochastic frontier analysis on panel data models often implicitly impose a restriction that information differences have no effect on the way risk-neutral decision makers utilize the same input bundle (Christopher *et al.*, 2010). The result is that informational differences are mistaken for differences in technical efficiency. The two specific effects that reflect information differences are the individual effects and the time effects. They are usually specified in stochastic frontier models in the manner that individual effects are time-invariant and do not interact with time effects, often in linearity or in parametric forms. However, when the individuals in the sample differ in technology and efficiency with differenced information, especially when such heterogeneity changes with time, the linear or parametric specification cannot fully describe the heterogeneity in the production function and may induce a bias in the measurement of technical efficiency. Conventional methods (either DEA or SFA) attribute the model misspecification errors to inefficiency (Fu, 2005; Balaguer-Coll *et al.*, 2007; Grösche, 2009; Joseph *et al.*, 2010; Battese and Coelli, 1992, 1995; Kumbhakar and Lovell, 2000; Wu 2003). Researchers have relaxed distributional assumptions in the error component and parametric assumptions in SFA to achieve a more reliable measurement of technical efficiency (Greene, 2005; Kneip and Simar, 1996; and Henderson and Simar, 2005).

The data set used in this study contains the thirty provinces in China for the period from 1985 to 2008. One can note that China during the sample period has experienced a systemic transition with heterogeneity of provinces and development periods. The regional effects and time effects should be given sufficient attention in measuring the technical efficiency of the economy. This paper provides a time-variant estimation of technical efficiency in China's post-reform economy by specifying and estimating a fully nonparametric stochastic frontier model with nonparametric individual and time effects (Henderson and Simar, 2005). A factor analysis on technical efficiency by using the Tobit regression will also be conducted.

Section 2 specifies the nonparametric model and presents the estimation method. Data and variables specification are illustrated in Section 3. Section 4 presents the empirical results of the frontier model and the measurement of the technical efficiency. Section 5 provides the specification test to show the suitability of the nonparametric model. Section 6 provides a factor analysis on the technical efficiency based on the Tobit estimation. Section 7 concludes the paper.

2. Fully Nonparametric Model Specification

The studies in Gong and Sickles (1992) and Christopher *et al.* (2010) show that the estimates of technical efficiency for the parametric panel data frontier model can be improved when the production function model is closer to the true underlying technology. In practice, the data generating process is unknown and so are the stochastic factors in the economic data. Hence a flexible model specification will give a more reliable result on frontier and efficiency estimates. In our sample period, production technology and efficiency in China has experienced uneven development among different provinces. A fully nonparametric stochastic model can thus give reliable technical efficiency estimates. We specify the nonparametric stochastic frontier model as follows:

$$y_{it} = f(x_{it}, i, t) + u_{it}, \quad i = 1, 2, \cdots, n; t = 1, 2, \cdots, T \tag{1}$$

where y_{it} is the logarithm of real gross regional product (RGRP) for province i in year t; x_{it} is the vector of the logarithm of the three inputs: capital (K), labor (L) and human capital (HC); $f(x,i,t)$ is the production function which is allowed to vary over each province and time period, and is nonparametric with input variables x, individual effects and time effects; u_{it} is the error term independent of x_{it}. As we know, human capital may have an impact on production through both direct and indirect channels (Barro and Sala-i-Martin, 1999; Benhabib and Spiegel, 2005; Vandenbussche *et al.*, 2006). Equally, the human capital embodied in the labor force can exert a direct and an indirect influence on aggregate production through technological innovation, imitation and adoption. Given that the impact channels are uncertain, it would be appropriate to allow human capital to enter the production function and interact with capital and labor inputs, individual and time effects in a nonparametric manner.

Model (1) can be estimated using the approach in Henderson and Simar (2005). Denote $\beta(x,i,t)$ as the first derivative of $f(x,i,t)$ with respect to x. By the Taylor expansion,

$$y_{it} = f(x,i,t) + (x_{it} - x)\beta(x,i,t) + o(|x_{it} - x|) + u_{it}, \tag{2}$$

where $o(|x_{it} - x|)$ is the higher-order term of $|x_{it} - x|$. Since we apply the local linear estimation, and the higher-order term is $o(|h_c|)$ as the bandwidth h_c of the continuous variable tends to zero, and hence the higher-order term can be merged into the error term and does not affect the consistency of the nonparametric function. Note that the frontier function includes unordered categorical variable i and ordered categorical variable t. To smooth them, the following kernel function is applied:

$$K_{ijts}(h_c, h_u, h_o) = \left(\prod_{r=1}^{q} k\left((x_{r,js} - x_r)/h_{cr}\right)\right) l_{u,ij} l_{o,ts}$$

where $k(\cdot)$ is the kernel for continuous input variables; $l_{u,ij}$ and $l_{o,ts}$ are the kernels for the individual variable i and the time variable t, defined as

$$l_{u,ij}=\begin{cases}1, & j=i,\\ h_u, & j\neq i\end{cases} \quad \text{and} \quad l_{o,ts}=\begin{cases}1, & s=t,\\ (h_o)^{|s-t|}, & s\neq t.\end{cases}.$$

As $h_u=0$, $l_{u,ij}=1\{j=i\}$ is the indictor function of province *i*, implying that only the data of province *i* are used in the estimation; as $h_u=1$, $l_{u,ij}\equiv 1$, the product kernel is unrelated to province *i*, implying that individual effects have been smoothed out. Now h_u is allowed to change continuously, and is combined with the above two special cases and plays a role in the smoothness of individual effects. In the similar way, h_o plays a role in the smoothness of time effects. We call $h_c=(h_{c1},\cdots,h_{cq}),h_u,h_o$ the smoothers or bandwidths for continuous variables, individual variable, and time variable, respectively. Let $X_{js}=(1,x_{js}-x)$. From (2), $\delta(x,i,t)\equiv(f(x,i,t),\beta(x,i,t)^{'})^{'}$ can be estimated by

$$\hat{\delta}(x,i,t)=\left(\sum_{j=1}^{n}\sum_{s=1}^{T}K_{ijts}(h_c,h_u,h_o)X_{js}^{'}X_{js}\right)^{-1}\left(\sum_{j=1}^{n}\sum_{s=1}^{T}K_{ijts}(h_c,h_u,h_o)X_{js}^{'}y_{js}\right). \quad (3)$$

The optimal bandwidth (h_c,h_u,h_o) can be determined by the least squares cross validation (LSCV) approach:

$$(h_{0c},h_u,h_o)=\arg\min CV(b_{0c},b_u,b_o)\equiv\sum\nolimits_{t=1}^{T}\sum\nolimits_{i=1}^{n}(y_{it}-\hat{f}_{-i}(x_{it},i,t))^2. \quad (4)$$

Here $\hat{f}_{-i}(x_{it},i,t)$ is the leave-one-out estimator of $f(x_{it},i,t)$ with bandwidths h_c, b_u and b_o, where b_{0c},h_u,h_o are positive constants, $h_c\equiv b_{0c}std(x)(nT)^{-1/(4+q)}$, and $std(x)$ denotes the sample standard deviation vector.

Following Henderson and Simar (2005), the estimate of technical efficiency for province *i* in time period *t* is defined as

$$TE_{it}=\exp\ \hat{f}(x_{it},i,t)-\max_{j=1,\cdots,n}\hat{f}(x_{it},j,t)\ . \quad (5)$$

Essentially the measure of technical efficiency compares the difference between the actual (estimated) outputs of province *i* and the maximum potential output produced by any other province in the sample for the same time period.

Besides the nonparametric specification in Model (1), we also present two other specifications of semiparametric and parametric models for comparison. The purpose is to know what will happen to the estimates when restrictive specifications on the technology are estimated. The two special cases are restricted forms of Model (1) with time-invariant production functions instead of time-variant ones. In the semiparametric case, the specification is

$$y_{it} = f(x_{it}) + \alpha - u_i + \varepsilon_{it},\ i = 1,2,\cdots,n;\ t = 1,2,\cdots,T \tag{6}$$

where $f(\cdot)$ is a nonparametric function of the inputs to be estimated, which is an averaged and time-invariant production function, and the fixed effects $\alpha_i = \alpha - u_i$ enter the model in a linear and additive form which is also time-invariant. The function $f(\cdot)$ can be estimated, denoted as $\hat{f}(\cdot)$, by the locally linear nonparametric kernel methods (Li and Racine, 2007). The parametric case is a particular case of the semiparametric form with $f(x_{it}) = x_{it}'\beta$:

$$y_{it} = x_{it}'\beta + \alpha - u_i + \varepsilon_{it},\ i = 1,2,\cdots,n;\ t = 1,2,\cdots,T \tag{7}$$

The parameter β, denoted as $\hat{\beta}$, can be estimated by the conventional within-estimator for panel data models with fixed effects. The technical efficiency for province i is defined as (Kneip and Simar, 1996)

$$TE_i = \exp(-\hat{u}_i), \tag{8}$$

where in a normalization form $\hat{u}_i = \max_i \hat{\alpha}_i - \hat{\alpha}_i$, $\hat{\alpha}_i = \sum_{t=1}^{T}(y_{it} - \hat{f}(x_{it}))/T$ in the semiparametric case, and $\hat{\alpha}_i = \sum_{t=1}^{T}(y_{it} - x_{it}'\hat{\beta})/T$ in the parametric case. We will apply specification tests only to the most suitable model in our empirical study.

3. Data and Variables

Despite the debate on the accuracy of macroeconomic data and the lack of a reliable alternative set of economic data in post-reform China, empirical studies have relied on reconstructed macroeconomic variables (Young, 2000; Rawski and Xiao, 2001;

Holz, 2006; Chow 2006).[1] Other than accuracy, critics have noted a number of problems in China's macroeconomic data. One concern is the transformation from the Soviet material product system (MPS) to the system of national accounts (SNA) as the former does not value "non-market" and "non-materials" output and services and another concern is the deficiency in China's national account and statistical practice (Maddison and Wu, 2008; Wu, 2000, 2003).[2] Others have concentrated on the estimation of the capital stock series, and that such detailed measures as the scrap rate and depreciation rate of the same capital equipment at different years are absent (Wu, 2007; Holz, 2006). A number of empirical studies agree that problems in the time series data may cancel out each other and that China's statistical reporting system and data reliability have improved over the years (Chow and Li, 2002; Li, 2003, 2009; Szirmai *et al*., 2005).

The data for China's thirty provinces and the construction of key variables used in this paper are elaborated in the Appendix. The thirty provinces that include the four autonomy areas and three municipalities under direct central administration are geographically divided into four regions. The Southern region composes of nine southern provinces, commonly known as the Pearl River Delta provinces of Fujian, Guangdong, Guangxi, Hainan, Jiangxi, Hunan, Sichuan (including Chongqing since 1997), Guizhou and Yunnan. The Eastern region consists of twelve provinces, including mainly provinces in the Yellow River and Yangtze River Delta regions of Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Shandong, Anhui, Henan, Hubei, Shanxi and Gansu. The Western region refers to the remote provinces of Inner Mongolia, Tibet, Shaanxi, Qinghai, Ningxia, and Xinjiang. The remaining three provinces in Northeastern region are Jilin, Heilongjiang and Liaoning, which consist of the traditional state-owned heavy industries. These four sub-regions in China are chosen in our study to reflect the geographical strength and economic growth concentration.

China's national and regional output figures can be obtained, respectively, from the

[1] China's GDP has been revised upwards by US$300 billion in December 2005. *South China Morning Post*, December 13 and 21, 2005, and January 13, 2006.

[2] For example, China's National Bureau of Statistics (NBS) reported in December 2004 that by incorporating non-agricultural activities, annual GDP estimates have been under-reported.

Statistical Yearbook of China and the various provincial statistical yearbooks. Scholars have used national income and sector output to construct China's physical capital stock (Jefferson *et al.*, 1996; Wu, 1995, 2008). One reliable method shown in Chow and Li (2002) and Li (2003) is Chow's (1993) estimation of China's 1952 physical capital stock. Based on the "accumulation" figures available up to 1978 in the official statistics and the additional comparable net investment and provincial depreciation figures since 1978, the construction of China's national and provincial physical capital stock series have been extended to 1998. While Li (2009) has repeated the construction exercise and extended the data to 2006, the analysis in this paper adopts the same steps and extends China's provincial physical capital stock to 2008. The data of the labor inputs are the total employed persons (in ten thousand persons) obtained from the *Statistical Yearbook of China.*

Human capital has been considered as an endogenous growth variable (Romer, 1990; Tamura, 2002, 2006; Turner *et al*., 2008). Similarly, there have been alternative methods in constructing human capital (Gemmell, 1996; Zhang *et al*., 2005; Chi, 2008). The inventory approach used in Wang and Yao (2003) measures China's human capital stock per capita in average years of schooling for the period 1984-2000. In Liu and Li (2006) and Li *et al*. (2009), the years of schooling are divided into six levels (primary education, junior secondary, senior secondary, vocational secondary, specialized secondary and higher education). The inventory-based construction of the human capital stock has been adjusted by inter-provincial migration and mortality rates from the estimated census data. Since 2004, the six levels of schooling have been reclassified into four levels of primary education, junior middle education (including regular junior middle and vocational junior middle education), senior middle education (including regular senior middle, vocational middle and specialized secondary), and higher education. Following Li (2009, Appendix), standard assumptions on the transition between different classifications are used so that national and regional human capital stocks per capita adjusted by employment figures can be updated to 2008 (see Appendix). Li *et al*. (2009, Table 3) reports that the estimation on China's human capital by the inventory method is similar to the estimation in Barro and Lee (2001), whose study has shown that China's human capital is lower than that of other Asian economies.

In order to eliminate the size effect of the provinces that may affect the measure of technical efficiency, we include in the denominator of each province's real gross regional product (RGRP), physical capital stock and labor inputs the province's total population. Kneip and Simar (1996) and Henderson and Simar (2005) have also made such an adjustment in their frontier models to measure technical efficiency. Table 1 provides the simple statistics for the data of the four variables. The coefficients of variation in the last column of Table 1 show that RGRP and physical capital stock have much larger degrees of variation than the other two variables in our sample.

Table 1 Summary Statistics of the Data (30 provinces: 1985-2008)

	average	min	max	stdev	coefficient of variation
RGRP/Population	2581.71	326.26	26576.64	2936.55	114%
Capital/ Population	9219.06	848.10	86385.38	11103.96	120%
Labor/ Population	0.51	0.36	0.82	0.07	15%
Human Capital	5.45	0.74	10.88	1.90	35%

Figure 1 reports the dynamic average performances of the four variables. One general observation is that these variables show obvious time trends in the sample period, especially since the late 1990s. The labor per capita variable has shown a clear structural break. The Eastern region has the highest average RGRP per capita. The Northeastern region has a similar level of RGRP per capita to the national average, whereas the Western and Southern regions have a lower level than the national average. Although the Northeastern region has the highest level of physical capital and human capital per capita, it has the lowest labor per capita. The differences in RGDP, level of physical capital stock and human capital per capita across provinces and regions show clearly that there are great variations in the development paths among the provinces in China's post-reform economy. The statistical evidences shown in Table 1 and Figure 1 hint that a flexible time-variant stochastic econometric model with individual effects and time effects may be required in order to estimate a reliable measure of technical efficiency for China's post-reform economy.

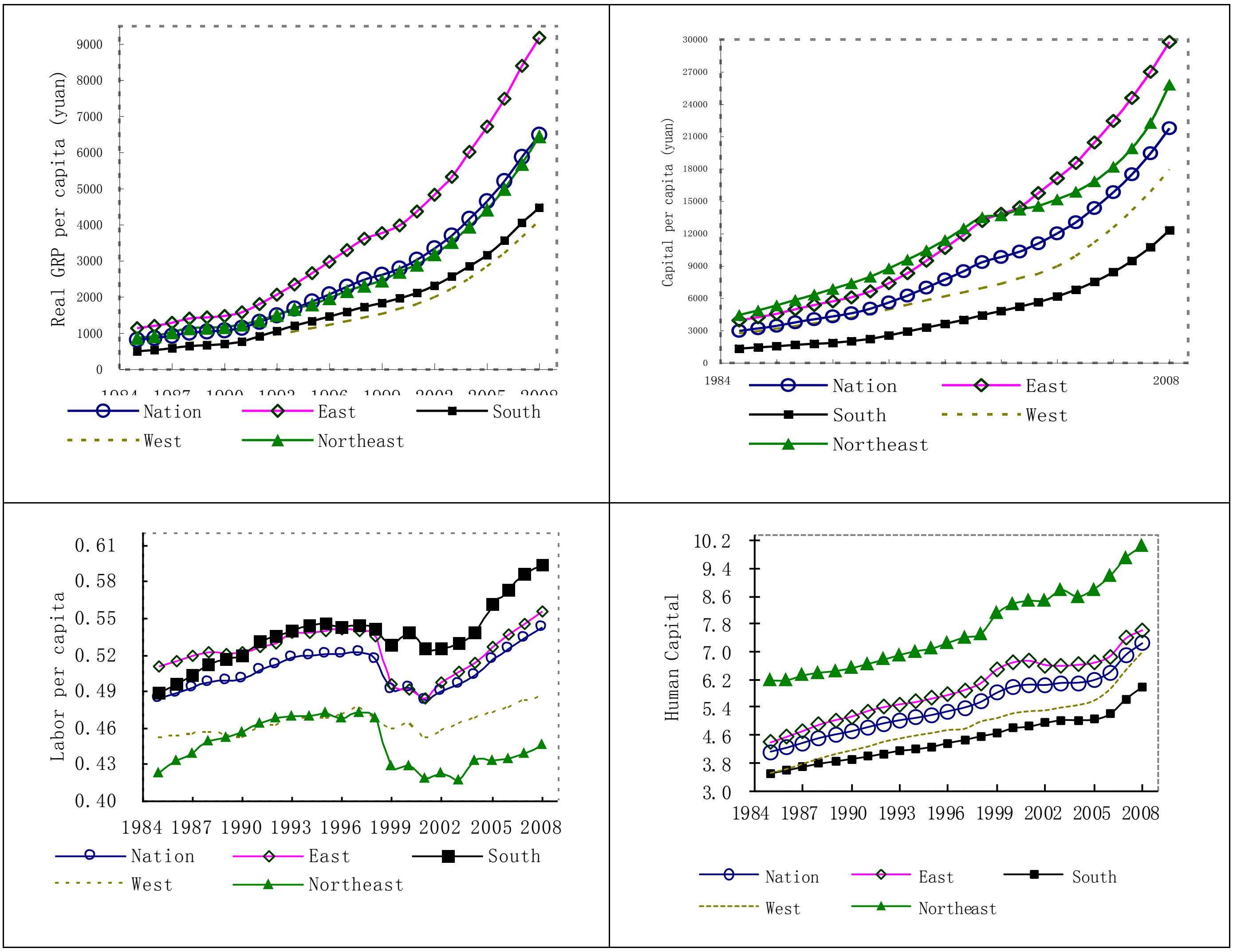

Figure 1 Dynamics of China's Average Real GDP or GRP per capita (1985-2008)

4. Estimation Results

In order to provide a comparison with the estimation of the nonparametric specification indicated in Model (1), we also specify two other restricted versions with time-invariant specification, namely, the semiparametric Model (6) and the parametric Model (7). All the variables are expressed in logarithms. The variables are adjusted for the time trend effect in the two restricted models, but not in the nonparametric Model (1) because the time effect has already been picked up by the categorical variable. This time-effect adjustment for dependent and independent variables in the time-invariant models is also used in Kneip and Simar (1996) and Henderson and Simar (2005). The technical efficiency for the two restricted versions is calculated from Model (8).

In the nonparametric estimation of Model (1) and Model (6), we select the fourth-order Gaussian kernel function $k(u) = \left(1.5 - 0.5u^2\right)\exp\left(-u^2/2\right)/\sqrt{2\pi}$ to alleviate the curse of dimensionality since the dimension of the input variables is three. By using the least squares cross validation (LSCV) approach shown in (4), the optimal bandwidths of the three continuous input variables are 0.492, 0.072 and 0.217, and the optimal bandwidths of categorical variable i and ordered categorical variable t are 0.153 and 1.035, respectively, for the estimation of Model (1).[3] The LSCV optimal bandwidths of the three continuous input variables for the local linear nonparametric estimation of the semiparametric Model (6) are 0.051, 0.046 and 0.041.[4]

We use R^2, the squared correlation coefficient between the dependent variable and the fitted value, to measure the goodness-of-fit for the estimated model. The R^2 values for the estimation of the three models are shown in the last column of Table 2, and the values given by parametric and semiparametric models are 0.38 and 0.48, respectively. The nonparametric estimation gives a large goodness-of-fit measure with $R^2 = 0.98$.[5]

Table 2 Estimation of Average Output Elasticity

	Capital	Labor	Human Capital	R^2
Parametric	0.6191	0.1475	-0.0949	0.3772
	(0.0948)	(0.0764)	(0.1009)	
Semiparametric	0.6513	0.2785	-0.1336	0.4828
	(0.0844)	(0.1053)	(0.1000)	
Nonparametric	0.7494	1.2211	0.5488	0.9829
	(0.0796)	(0.4431)	(0.2664)	

Note: The values in parenthesis are the bootstrapped standard errors of the estimates. The replications are 400.

3 In order to examine the effect of the kernel selection on the estimation results, we also apply the second-order and the sixth-order Gaussian kernel for the nonparametric estimation. It is found that the results are quite similar. Hence we only report the results from the fourth-order Gaussian kernel.

4 The optimal bandwidths chosen in the nonparametric estimation of the semiparametric model (6) are much smaller than those in the nonparametric estimation of the nonparametric model (1). This is due to the fact that the variables have been adjusted for the time effect in the semiparametric model (6) but not in the nonparametric model (1). However, the categorical variable *t* in nonparametric model (1) picks up the time effect with an optimal bandwidth of 1.035.

5 Note that the R^2 from the nonparametric estimation is not suitably compared with the R^2s from the parametric and semiparametric estimations since they have different dependent variables. For the latter two models, the dependent variables have been dealt with by a time-effect adjustment since they are specified with a time-invariant restriction.

Table 2 shows the sample average of the output elasticity estimates of the three inputs in the three specification models and their corresponding bootstrapped standard errors. In the parametric and semiparametric models, the coefficient estimates of capital and labor are positive and significant, while the coefficient estimates of human capital, though insignificant, are negative and unexpected. However, the elasticity estimates of the three inputs in the nonparametric model are positive and significant, which can provide expected and meaningful economic explanation. When compared to other studies, for example, by Young (2003) and Li (2009) who do not estimate the output elasticity of inputs by using per capita output and inputs, our finding shown in Table 2 is that the output elasticity of labor, instead of the elasticity of capital, is the largest of the three inputs.

Table 3 presents the estimates of the yearly average technical efficiency of the 30 provinces. The average time-invariant technical efficiency results are calculated according to the parametric Model (7) and semiparametric Model (6) using formula (8), while the average time-variant technical efficiency results are calculated according to the nonparametric Model (1) using formula (5).

Table 3 shows a large discrepancy in the ranking of provinces between the semiparametric and parametric models for a majority of provinces. Only the three provinces of Beijing, Heilongjiang and Jiangxi are ranked in almost the same order between the two estimates. Such a result, along with the weak goodness of fit and the meaningless and insignificant coefficient estimates of human capital, suggests that the time-invariant assumption shown by the linear parametric and semiparametric models may be incorrect. The less restrictive nonparametric time-variant model can correctly be used to calculate the time-variant technical efficiency. Indeed, many of the rankings in the nonparametric model differ significantly from those in the parametric and semiparametric models.

Table 3 Average Technical Efficiency and Province Ranking

Province	Parametric		Semiparametric		Nonparametric		DEA	
	TE	rank	TE	rank	TE	rank	TE	rank
Beijing	0.2309	29	0.9901	28	0.7988	27	0.6941	17
Tianjin	0.2840	27	0.9905	24	0.8924	21	0.8474	8
Heibei	0.7621	8	0.9980	3	0.9794	9	0.9252	5
Shanxi	0.6185	16	0.9903	25	0.8478	25	0.6018	24
Inner Mongolia	0.6267	13	0.9923	17	0.9504	15	0.7031	16
Liaoning	0.2576	28	0.9922	18	0.6885	30	0.6123	23
Jilin	0.6204	15	0.9864	30	0.9153	19	0.7496	15
Heilongjiang	0.6294	12	0.9930	12	1.0000	1	0.8059	11
Shanghai	0.1839	30	0.9931	11	0.9575	14	1.0000	1
Jiangsu	0.4151	25	0.9917	19	0.9598	13	1.0000	2
Zhejiang	0.4270	24	0.9952	6	0.9954	6	0.8626	7
Anhui	0.7821	5	0.9934	9	0.9924	8	0.7610	14
Fujian	0.6014	17	1.0000	1	1.0000	2	0.8423	9
Jiangxi	0.7683	7	0.9935	7	0.9682	11	0.7624	13
Shandong	0.5856	18	0.9934	10	0.9324	16	0.8685	6
Henan	0.7571	9	0.9915	20	0.8625	24	0.6927	19
Hubei	0.6775	11	0.9929	14	0.9997	3	0.8095	10
Hunan	0.8760	3	0.9902	27	0.9945	7	0.7865	12
Guangdong	0.5441	22	0.9955	5	0.9784	10	0.9967	3
Guangxi	1.0000	1	0.9929	15	0.9032	20	0.6935	18
Hainan	0.5446	20	0.9957	4	0.8680	23	0.6185	22
Sichuan	0.7820	6	0.9912	22	0.9976	4	0.9911	4
Guizhou	0.9786	2	0.9890	29	0.9154	18	0.5914	25
Yunnan	0.8543	4	0.9924	16	0.9671	12	0.6653	20
Tibet	0.3752	26	0.9999	2	0.9967	5	0.3878	30
Shaanxi	0.6227	14	0.9915	21	0.8404	26	0.5638	27
Gansu	0.6838	10	0.9903	26	0.9310	17	0.6497	21
Qinghai	0.5445	21	0.9912	23	0.7565	28	0.4713	28
Ningxia	0.4996	23	0.9930	13	0.7558	29	0.4506	29
Xinjiang	0.5496	19	0.9935	8	0.8740	22	0.5793	26

The nonparametric time-variant model estimation provides more information on the provinces and time dependent structure of the efficiencies. Appendix Table A1 reports the yearly technical efficiency scores of all provinces based on the nonparametric Model (1) and the formula (5). The scores show that the two provinces of Heilongjiang and Fujian are technically efficient in all years during the sample period. A total of thirteen provinces (Beijing, Shanxi, Liaoning, Jilin, Henan, Guangxi, Hainan, Guizhou, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang) are not technically efficient in any year; the remaining 15 provinces are technically efficient in at least one time period. Beijing ranked 27th in technical efficiency and is less efficient than many other provinces.

It can be calculated from Appendix Table A1 that 29.7 percent of observations (720 observations from 30 provinces in 24 sample years) have attained technical efficiency. The coefficient of variation for technical efficiency estimates is 10.6 percent, which shows that the difference of technical efficiency among the provinces should not be ignored. Such a finding is not available from the time-invariant parametric or semiparametric models.

Figure 2 presents the dynamics of the average technical efficiency for the 30 provinces in the sample period. Economic liberalization in the early years of economic reform and openness has probably led to the initial increase in technical efficiency. The initial increase in technical efficiency, however, was not sustainable. The technical efficiency declined rapidly to the lowest level in 1992 before it bounced back and reached new peaks in 1998 and 2006.

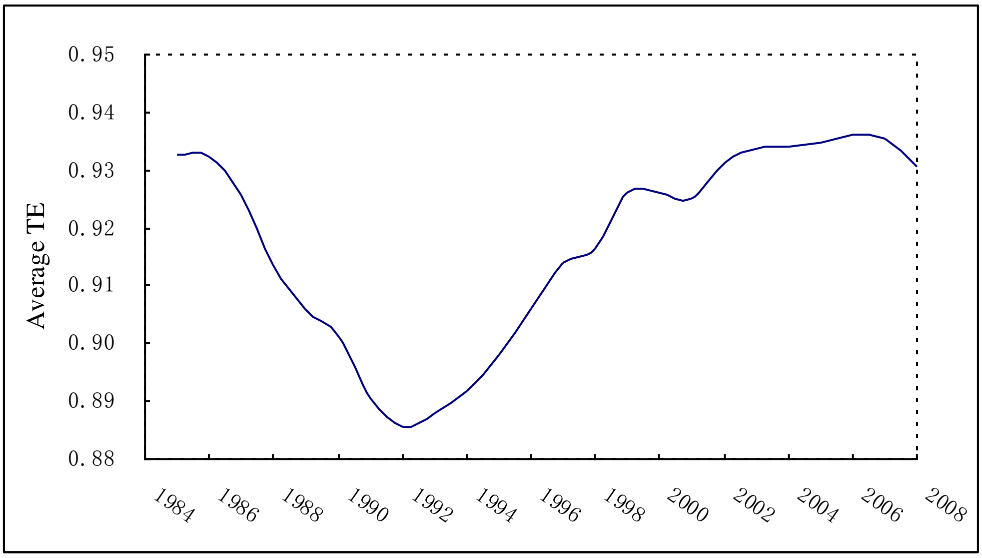

Figure 2 The Dynamics of Technical Efficiency

Figure 3 shows the regional variation in the dynamics of average technical efficiency. At the national level, and despite the marginal decline between 1985 and 1992, the overall trend has been a gradual increase in technical efficiency. Both the Eastern and Southern regions have shown a better performance than the national average. Provinces in the Western and Northeastern regions have shown a lower level of efficiency than the national average. Provinces in the Northeastern region have shown a lowest level of technical efficiency before 1994, but since then, it has overtaken the Western region. Although there has been much attention and emphasis on the economic development in the Western region, its technical efficiency has remained backward, probably due to the faster economic development in the Eastern and Southern regions that had made the interior regions unattractive. Technical efficiency tends to be higher than the national average in the Eastern and Southern regions, which historically have been the most developed regions in China.

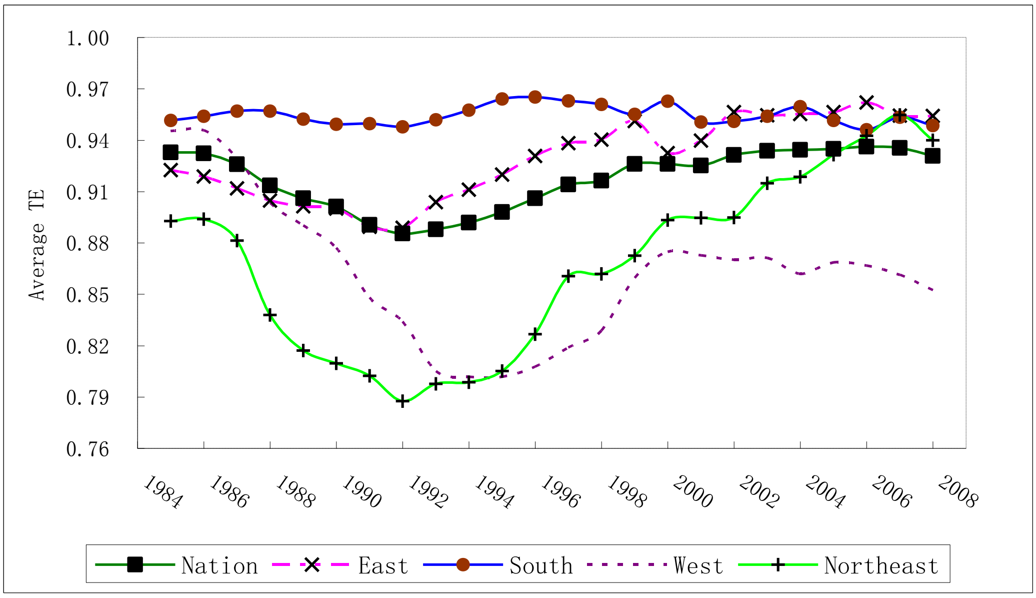

Figure 3 The Dynamics of Average National and Regional Technical Efficiency

5. Model Specification Test and Discussion

The semiparametric Model (6) and the linear parametric Model (7) assume time-invariant specifications in the estimation of technical efficiency, while the nonparametric Model (1) allows a flexible production specification with time-variant production technology. We have shown that the efficiency rankings among provinces in China differ greatly in the different approaches used to measure technical efficiency, and that the nonparametric specification is most suited to our sample. For a rigid analysis one needs to present a specification test whether this is acceptable or not.

This section presents two tests for model specification. The first test is to choose between (6) and (7). The null hypothesis is linear parametric Model (7) and the alternative is semiparametric Model (6). The second test is to choose between (1) and (6). The null hypothesis is semiparametric Model (6) and the alternative is nonparametric Model (1). We apply the test approach in Henderson *et al*. (2008). The test statistics for the two tests are, respectively,

$$I_n^{(1)} = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\left(x_{it}'\hat{\beta} - \tilde{f}(x_{it})\right)^2 \text{ and } I_n^{(2)} = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T}\left(\tilde{f}(x_{it}) - \hat{f}(x_{it}, i, t)\right)^2,$$

where $\hat{\beta}$ is a consistent estimate of the coefficient vector in (7), while $\tilde{f}(\cdot)$ and $\hat{f}(\cdot, i, t)$ are the consistent estimators of (6) and (1), respectively. Under the corresponding null, statistics $I_n^{(1)}$ and $I_n^{(2)}$ converge to zero in probability; under the alternatives, they both converge to positive constants. Here we use bootstrap method to approximate the asymptotic distribution and obtain the probability value (p-value) of each test, where the bootstrap replicate is 600. The values of $I_n^{(1)}$ and $I_n^{(2)}$ are 2.1113 and 3.9936 with the corresponding bootstrapped p-values of 0.0317 and 0.0025, respectively. The test results show that the nulls are rejected at a 5 percent significant level, and imply that the final model we should apply in our study is the nonparametric Model (1). This justifies the use of fully nonparametric model specification and estimation and further reconfirms the analysis on technical efficiency.

It would be interesting to compare the technical efficiency estimate from the nonparametric Model (1) and the technical efficiency measure from the data envelope analysis (DEA) approach though the two types of models are not nested since DEA is deterministic and does not allow for noise. The last column in Table 3 provides the TE scores and rankings based on the DEA approach. There also exists a large difference between the two kinds of score rankings. The DEA is essentially a descriptive tool that allows the analysis of the observed technology with deterministic but nonparametric frontiers where no statistical noise or random disturbance for the data is allowed (Kneip and Simar, 1996; Monchuk *et al*, 2010). However, neither output elasticity of the inputs nor inference is available from DEA.[6]

To compare the technical efficiency score rankings from different approaches, we calculate the correlation of the rankings between the nonparametric and the other models. The correlation coefficients between the nonparametric model and the two time-invariant models are only 0.30 and 0.44, respectively, while the correlation between the rankings in the nonparametric case and the DEA case is 0.59. This implies that the production function form and the time-variant characteristics in the technology are important in measuring technical efficiency in China's post-reform economy.

6 Factor Analysis of Technical Efficiency: Tobit Model of Inefficiency

The calculated technical efficiency scores based on the fully nonparametric stochastic frontier production model with individual effects and time effects are not affected by the specific function form and allow for time variant, and hence can theoretically minimize the loss due to the econometric misspecification of the frontier model. The estimates and the specification tests in Sections 4 and 5 justified the nonparametric model specification and the corresponding technical efficiency scores for the China's economy. These reliable efficiency scores can further be applied in the factor analysis of efficiency by investigating the determinants of technical efficiency because the results can be used for policy decisions aimed at improving economic performance.

In this study we use the customary two-stage procedure for the factor analysis of efficiency (Chilingerian, 1995; Kirjavainen and Loikkanen, 1998). In the first stage, the technical efficiency (TE) scores are obtained from the time-variant production technology. In the second stage, we explain the technical efficiency by using some relevant factors not directly included in the nonparametric Model (1). As defined in (5), the efficiency score is essentially bounded between zero and one, making the explained variable (namely, TE) a limited dependent variable. Also, as pointed out in Section 4,

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[6] Monchuk *et al*. (2010) regard the DEA-measured efficiency score as a sample from the population and specify a truncated regression model with this score as the dependent variable to conduct the factor analysis of TE. The bootstrap method is then used to construct the confidence interval of the coefficients estimate of the factors.

29.7 percent of the observations in our sample attained technical efficiency. That is to say, the values of the technical efficiency in these sub-samples are all equal to 1. This implies that the Tobit regression model in which the dependent variable is censored is more suitable in the factor analysis of technical efficiency.[7] Specifically, we transform the efficiency scores by taking their reciprocal minus one:

$$NTE_{it} = \frac{1}{TE_{it}} - 1$$

where TE_{it} is province i's technical efficiency in time t calculated from (5) based on the estimation of the nonparametric Model (1), and NTE_{it} is the corresponding inefficiency variable. This normalization is in fact a transformation from efficiency to inefficiency, assigning the best provinces (with $TE_{it} = 1$) zero and the inefficient provinces (with $0 < TE_{it} < 1$) a positive number. The transformation is only for computational convenience since the Tobit model often assumes a censoring point at zero. The inefficiency variable, NTE_{it}, valued in $[0, \infty)$, will be taken as the dependent variable in our Tobit regression.

There are many factors affecting technical efficiency in the China's economy. For the data available from the various issues of the *Statistical Yearbook of China*, a total of seven determinants of efficiency are chosen as the explanatory variables for the efficiency analysis.

First, inequality in the development between urban and rural areas and the urbanization level within a province in China are two important factors which can influence efficiency. China is committed to a long-term plan of building a moderately well off society for all citizens. This necessarily requires a coordinated development between urban and rural areas, a break down in the city-country dualistic structure, and a reallocation of surplus rural labor. The urban-rural inequality is expected to induce inefficiency and the urbanization is expected to reduce inefficiency. We use the income

[7] See Chilingerian (1995) for a detailed discussion about blending efficiency measurement approach with Tobit regression.

ratio of urban-rural household (URD, denoted as z_1) as the proxy variable for the urban-rural inequality. The urbanization (URBANIZE, denoted as z_2) is approximated by the percentage of the urban population in the total population of the province.[8]

Second, the extent of privatization that serves as a reform engine in the transition from a planned to a market economy in post-reform China could enhance flexibility in economic development.[9] In our study privatization is represented by the ratio of employed persons in non-state-owned units to the total employed (REFORM, denoted as z_3). The effect of REFORM on efficiency will be tested in our study.

Third, the factors related to openness in an economy are thought to affect efficiency (Wei *et al.*, 2001). Two kinds of important factors on openness are international trade and foreign direct investment (FDI) (Li and Zhou, 2010). The ratio of trade (sum of import and export) to gross regional product (TRADE/GRP, denoted as z_4) serves as a proxy for international trade. The ratio of FDI in fixed assets (including the funds from Hong Kong, Macao and Taiwan) to gross regional product (FDI/GRP, denoted as z_5) is used as a proxy for foreign direct investment. Although openness in an economy is thought to affect efficiency, there is no clear confirmation of the hypothesis that countries with an external orientation benefit from greater efficiency (Iyer *et al.*, 2008). We also test the effect of openness on efficiency in China's economy.

Fourth, the greater provision of infrastructure is expected to enhance technical efficiency. Since available data on transportation reflects the extent of infrastructure provision in China's national economy, we use the geometric average of the length of railway in operation and the length of highways per squared kilometer in a province's land area (INFRAS, denoted as z_6) as a proxy variable for infrastructure.[10] Inadequate transportation systems would hinder the movement of coal to the users, the transportation of agricultural and light industrial products from rural areas and factories to urban areas, and the delivery of imports and exports. Therefore, underdevelopment in

[8] Due to data limitation, URD is regarded as a proxy variable for the urban-rural inequality. This proxy variable may favor Beijing, Shanghai and other city provinces as they have a larger proportion of urban population than other non-city provinces. To deal with this discontentedness, we introduce URBANIZE as a control variable to partial out the effect of the urban-rural inequality on technical efficiency. We would like to thank the anonymous referee for this comment.

[9] Whether or not privatization has increased technical efficiency in developing countries has been debated in Okten and Arin (2006).

[10] Wu (2000, 2003) also specified a similar proxy.

the transportation system can constrain the pace of economic development.

Fifth, in contrast to FDI which reflects foreign investments, domestic investment in a region should affect the performance and efficiency of the local economy. We illustrate the domestic investment by the proportion of domestic fixed assets investment to gross regional product (INV/GRP, denoted as z_7).

Finally, the geographic factor may affect technical efficiency. Historically, there has been serious unevenness in regional development in China (Huang *et al.*, 2003). The geographic factor includes the between-region inequality in development and other observable regional heterogeneities. For example, in post-reform China, the coastal areas had already become more developed than the interior areas. We define 4 geographic dummy variables:

EAST = 1, if the province is from Eastern China; 0, otherwise;

SOUTH =1, if the province is from Southern China; 0, otherwise;

WEST = 1, if the province is from Western China; 0, otherwise;

NORTHEAST= 1, if the province is from Northeastern China; 0, otherwise.

In the regression, the Northeastern region is taken as the baseline region. The Tobit model for technical inefficiency is specified as

$$NTE_{it} = \max\{\alpha + z_{it}'\delta + \left(Tz_{it}'\right)\theta + D_i'\gamma + v_{it},\ 0\}.$$

That is,

$$NTE_{it} = \begin{cases} \alpha + z_{it}'\delta + \left(Tz_{it}'\right)\theta + D_i'\gamma + v_{it}, & \text{if } NTE_{it} > 0; \\ 0, & \text{if } NTE_{it} = 0, \end{cases}$$

where $z_{it} \equiv (z_{1it}, \cdots, z_{7it})'$ is the vector of the seven factors illustrated above; $Tz_{it} \equiv (t, tz_{1it}, \cdots, tz_{7it})'$, $D_i \equiv (EAST_i, SOUTH_i, WEST_i)'$; α is the intercept; δ, θ and γ are parametric vectors. A negative coefficient parameter implies a positive effect of the corresponding factor on technical efficiency. The error term v_{it} satisfies $v_{it}\,|_{z_{it}, D_i} \sim (0, \sigma^2)$. The Tobit model can be estimated by the maximum likelihood method (Amemiya, 1984; Wooldridge, 2002). Since the data for Tibet and some of the factors prior to 1990 are not available, the sub-sample used for the Tobit estimation excludes

Tibet and covers the period 1990-2008. A total of 31.2 percent of observations in this sample has attained technical efficiency.

Table 4 reports the maximum likelihood estimation results of the Tobit model when the error term is distributed as a normal distribution[11]. The marginal effect of each factor on technical efficiency is equal to the corresponding coefficient estimate times the ratio of inefficiency (Wooldridge, 2002). In our sample, the ratio is 100-31.2=68.8%. The coefficient estimate of the time variable t is negative but insignificant, which shows that the technical efficiency generally increases with time, albeit statistically insignificant. However, whether or not the time effects of technical efficiency in China's post-reform economy are positive depends also on the interaction terms of the seven factors with the time variable t. Although only two of the seven coefficient estimates of the interaction terms are significant at the 5 percent level (or four coefficient estimates are significant at the 10 percent level), the joint test for all the seven coefficients equal to zero is significant, as shown in Table 5: Row 1. This implies that the time effects on technical efficiency are jointly and significantly related with the seven factors.

Table 5 also presents some other joint tests for the coefficients of time variable and their interaction with the other factors Except the effect of REFORM, the estimates of the effects of all other factors on technical efficiency with time are jointly significant in the usual significant level, as shown in Rows 3 to 10 in Table 5. The last column in Table 5 presents the implication for each factor analysis of TE.

Rows 1 and 2 in Table 5 show that the time effect of TE is jointly significantly contingent on the seven factors, though the coefficient estimates of URD, URBANIZE and REFORM are marginally significant at the 10 percent or 15 percent significant level, as shown in Table 4. The China's economy has been experiencing a transition from the original planned economy to a market economy with particular characteristics. The technical efficiency path in economic growth should be significantly determined by a mixture of miscellaneous factors. Our finding on the time effect of TE among China's provinces is consistent with this fact.

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[11] The Tobit model is also estimated when the error term is specified as a logistic or extreme value distribution, each of which gives the same explanation as in Table 4.

The urban-rural inequality (URD) has a significant but negative effect on TE since 0.0453+0.0043t is always positive, as shown Row 3 in Table 5. This shows that a decrease in income difference between rural and urban areas within a province can enhance efficiency improvement.[12]

Table 4 Estimation Results of Technical Inefficiency from the Tobit Model

	coefficient estimate	standard error	p-value
URD	0.0453	0.0277	0.1021
URBANIZE	-0.1832	0.1135	0.1066
REFORM	-0.2522	0.1719	0.1423
TRADE/GRP	0.1982	0.0465	0.0000
FDI/GRP	-1.4807	0.5065	0.0035
INFRAS	1.5733	0.3746	0.0000
INV/GRP	0.5566	0.1981	0.0050
t	-0.0184	0.0147	0.2099
URD × t	0.0043	0.0026	0.0962
URBANIZE × t	0.0018	0.0127	0.8859
REFORM × t	0.0074	0.0171	0.6637
TRADE/GRP × t	-0.0180	0.0049	0.0003
FDI/GDP × t	0.0988	0.0586	0.0917
INFRAS × t	-0.0050	0.0276	0.8557
INV/GDP × t	-0.0315	0.0133	0.0177
EAST	-0.2104	0.0270	0.0000
SOUTH	-0.2064	0.0300	0.0000
WEST	0.0142	0.0293	0.6263
INTERCEPT	0.1988	0.1519	0.1908
SCALE: σ	0.1386	0.0053	0.0000
Pseudo R-squared		0. 5051	
Log likelihood		92.4386	

[12] The inequality indicator URD is only used to express the urban-rural income difference within a province. Hence it does not give a full-scale measure of inequality between the rural and the urban in China. The finding should be interpreted with caution since the relationship between URD and TE may not be well generalized to the true relationship between inequality and TE in China economy.

Table 5 Factor Analysis of Marginal Effects on Technical Inefficiency

	Marginal effect on technical inefficiency	Estimate ≈ the following formula times 68.8%	P-value for the joint test	Implication on technical efficiency
1	Interaction effect of factors and time	$0.0043z_1+0.0018z_2+0.0074z_3-0.0180z_4+0.0988z_5-0.0050z_6-0.0315z_7$	0.0000	The time effects on technical efficiency are jointly and significantly related with the seven factors.
2	Time Effect	$-0.0184+0.0043z_1+0.0018z_2+0.0074z_3-0.0180z_4+0.0988z_5-0.0050z_6-0.0315z_7$	0.0000	The time effect on TE decreases with URD, URBANIZE, REFORM and FDI/GRP but increases with TRADE/GRP, INFRS and INV/GRP. The time effect is significantly contingent on these factors jointly.
3	URD (z_1) Effect	0.0453+0.0043t	0.0000	The urban-rural inequality is not beneficial to improvement of TE
4	URBANIZE (z_2) Effect	-0.1832+0.0018t	0.0134	Urbanization is beneficial to the improvement of TE, and this positive effect decreases with time insignificantly.
5	REFORM (z_3) Effect	-0.2522+0.0074t	0.2235	Privatization is beneficial to the improvement of TE, but this positive effect decreases with time and it is statistically insignificant.
6	TRADE/GRP (z_4) Effect	0.1982-0.0180t	0.0001	Trade is not beneficial to the improvement of TE, but the negative effect decreases with time significantly.
7	FDI/GRP (z_5) Effect	-1.4807+0.0988t	0.0037	FDI is beneficial to the improvement of TE in the early stage, but this positive effect decreases with time significantly.
8	INFRAS (z_6) Effect	1.5733-0.0050t	0.0000	Infrastructure level is not beneficial to improvement of TE in the early stage, but this negative effect decreases with time significantly.
9	INV/GRP (z_7) Effect	0.5566-0.0315t	0.0194	Domestic investment is not beneficial to the improvement of TE, and this negative effect decreases with time significantly.
10	Region Effect	(East, South, West) = (-0.2104,-0.2064,0.0142) compared with Northeast	0.0000	Geographic factors have significant effects on TE. The Eastern and Southern regions have more TE than the Northeastern while the Western has less.

It can also be seen that URBANIZE is beneficial to the improvement of TE since the estimated effect of urbanization on inefficiency is negative ($-0.1832+0.0018t < 0$). This positive effect of urbanization on technical efficiency is statistically significant (the probability value of the joint test is very small, shown in Row 4 of Table 5). Although the effect decreases with time, it is both economically and statistically insignificant since the coefficient estimate of "URBANIZE × t" is small and statistically insignificant (see Table 4). The neoclassical analysis would argue that urbanization enhances efficiency in two ways. On the one hand, people migrate to cities and obtain better employment or wages, and hence higher savings, which in turn is converted into productive investment capital and the technical efficiency can then be improved. On the other hand, higher incomes also lead to changes in the composition of demand from agricultural to manufactured goods. The demand of manufactured goods increases technology and productivity growth.

As shown in Row 5 in Table 5, the REFORM factor shows a positive, albeit insignificant, effect on technical efficiency. The REFORM factor is beneficial to TE improvement ($-0.2522+0.0074t < 0$), but the effect on TE will finally become negative with the development of privatization (when $t>34$, $-0.2522+0.0074t >0$). Although the effect of privatization on efficiency is ambiguous in both theoretic and empirical literatures (Okten and Arin, 2006), it is positive in our estimation. In China, privatization has emancipated the productive forces which have been fettered by the planned economy for a long time. Privatization can induce competition and enhance productivity that eventually can contribute to efficiency improvement. However, even though the effect is large, it is not statistically significant in our estimation since the p-value of the test is 0.2235.

Trade and foreign investment can give rise to either positive or negative efficiency (Loungani and Razin, 2001). Our estimates and tests in Rows 6 and 7 of Table 5 show that in the early development stage TRADE/GRP has a negative and significant effect on efficiency ($0.1982-0.018t>0$ when $t<12$), while FDI/GRP has a positive and significant effect ($-1.4807+0.0988t<0$ when $t<15$). In the later development stage, the effects will drive off in the reverse direction. One can see from Table 4 that the time effects of the two influences from the two variables are significant at 1 percent level and

10 percent level, respectively. This may be due to two reasons. One is the problem of endogeneity in the measurement of openness with the ratio of trade to GRP in the growth literature. The other is that trade has been overemphasized in the economic transition, while efficiency has artificially been ignored somewhat in China. For the China's economy to sustain a high-speed economic development, reform will have to become a long-term policy, whereas international trade can be adjusted to suit for growth and efficiency. Foreign direct investment can have an indirect effect on the domestic economy via positive spillovers and competition (Blomstrom and Persson, 1983). Our finding implies that, even though FDI have an important and positive effect on TE in the China's economy, it should be further encouraged to neutralize the downward trend of the effect.

The provision of infrastructure has a negative and significant effect on technical efficiency (1.5733-0.005t>0), which implies that regional inequality in infrastructure development in China has hindered improvement in technical efficiency. Although this is inconsistent with the expectation about the positive effect of infrastructure on TE, it is the regional bottleneck that constrains economic growth in China. To keep a balanced growth among different regions, China should expand development in the underdeveloped regions, especially the underprivileged regions in her western provinces.

As regards to the domestic investment factor, our finding shows that it is only when $t \geq 18$ that the effect of domestic investment on technical efficiency will be positive (0.5566-0.0315t < 0). Thus, domestic investment is not beneficial to the improvement of TE in the early stage of development (t<18). However, the time effect of the negative marginal influence will significantly decrease with time (-0.0315<0). As we have found, the effect of FDI on TE is contrary to the effect of domestic investment. The two kinds of investment have direct and significant effects on TE for capital accumulation of the local economy, but the direction of their effects is opposite to each other.

Finally, the result of Row 10 in Table 5 shows that geographic factors have a joint significant effect on TE. The geographical location of a province in China can often determine its transport facilities and the availability of information, technology, intermediate inputs and other resources. Thus, different geographic locations among the provinces have different effects. When compared to the Northeastern region, the Eastern and Southern / Western regions have a higher / lower technical efficiency. Consistent with Figure 3, the ranking of technical efficiency for the four regions in China's economy is: East > South > Northeast > West.

6. Conclusion

This study uses a flexible stochastic production function to estimate technical efficiency in China's post-reform economy. A fully nonparametric time-variant stochastic frontier model has been specified to allow for province effects and time effects to enter the production function with other inputs in a nonparametric way. The generalized kernel estimation is applied to smooth both the continuous input variables and the categorical unordered provinces and the ordered time periods. The flexibility in the production functional form and the manner of individual and time effects that entered into the production model can minimize the loss in the measurement of technical efficiency, lead to robust estimates of the frontier function and produce a reliable measure of technical efficiency. Model specification tests and estimates show that the fully nonparametric stochastic model is more suitable for our sample. The average output elasticity of labor is larger than those of capital and human capital, which are all positive.

The measure of TE based on nonparametric estimation shows that the average technical efficiency in China has declined considerably in the mid-1980s, but has increased since 1992. Technical efficiency tends to be higher than the national average level in both Eastern and Southern regions. Although China has emphasized a lot on the development of the Western region, its technical efficiency has remained low. Unexpectedly, Beijing, being the capital of China, shows a lower technical efficiency than most other provinces.

The estimation of the Tobit model of technical inefficiency shows that the time effects of technical efficiency in China's post-reform economy are significantly contingent on the seven factors shown in Table 4. With the exception of privatization, the marginal effects of all the other factors also have significant time effects. There exists regional difference in technical efficiency. To maintain a sustainable, high-speed development, China should continue to reform and adjust its international trade to suit growth and efficiency improvement. Foreign direct investments have an important and large positive effect on technical efficiency, but it should be further encouraged to neutralize the downward trend of the effect. China should attach great importance to its infrastructure policy and reappraise the infrastructure development policy to give a positive effect on technical efficiency.

The empirical findings in this paper have improved the discussion on China's productivity analysis, echoed on such recent discussions as regional inequality, disparity in growth inputs and human capital development in China's post-reform economic development (Wu, 2008; Li, 2009; Li and Liu, 2011; Chang, 2002; Fleisher and Zhao, 2010; Liu and Li, 2006; Chi, 2008; Li *et al*., 2009). Furthermore, the empirical findings in this paper provide a reflection on the efficiency in financial issues, such as bank loans and corporate bonds development, on economic policy decisions, such as the pace of market liberalization and privatization of enterprises, and on infrastructural and civic development, such as eradication of informal economic activities.

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Appendix

Data Sources and Construction of Variables

All China data used in this paper are available from the corresponding author. The major sources of national data are obtained from the various issues of *Statistical Yearbook of China* (SYC), the *Comprehensive Statistical Data and Materials in 50 Years of New China* (1999) (CSDM) and *Statistics on Investment in Fixed Assets of China 1950-2000* (SIFAC). The sources of provincial data including employment figures come from various provincial statistical yearbooks (PSYC). The sources for some individual provinces come from their "fifty years" (50 yrs) yearbooks, including *Fifty Years of Beijing, Fifty Years of Jilin*, *Hebei Economic Statistics 1949-2001*, *Shanxi 50 Years 1949-1999* and *Xinjiang 50 Years 1949-1999*. Other sources include *Brilliant Inner Mongolia*, *Heibei Economic Yearbook* and *Tibet Social and Economic Statistical Yearbook 1992*.

Chow and Li (2002), Li (2003) and Liu and Li (2006) applied the following three identities to derive China's national capital stock: $GDP_t = C_t + GI_t + NX_t$, $K_t = K_{t-1} + RNI_t$, and $RNI_t = RGI_t\ [(GI_t - Dep_t\ )/GI_t]$. GDP_t is Gross Domestic Product, C_t is consumption, NX_t is the net export of goods and services and GI_t is nominal investment. Physical capital stock is K_t, RNI_t is real net investment, and RGI_t is real gross investment. Dep_t is national depreciation figure, and the subscript t represents the time period. Real consumption is nominal consumption deflated by the consumption price index, while the implicit GDP deflator is used to derive the real value of net exports. Provincial depreciation figures are adjusted to derive the depreciation figures. The national variables of GDP index, GDP (Production), Consumption Price Index, GDP (Expenditure), consumption expenditure and net export expenditure are obtained from the latest issue of SYC. Employment figures for all provinces can be found in CSDM. The sources of the three provincial variables of GDP index, gross investment and labor are collected mainly from the 2007 issue of PSYC and 50 yrs. The steps used to construct the national capital stocks are similarly applied to the construction of the provincial capital. The provincial GDP deflator is used throughout. Provincial real net investment (*PRNI*) is provincial real gross investment (*PRGI*) less provincial depreciation.

Depreciation figures of individual provinces are available in the various issues of SYC for the periods 1993-1994 and 1996-2008. Some PSYC provide also the 1995 and pre-1993 depreciation figures. Tianjin, Shanxi, Anhui, Qinghai and Hubei have their depreciation figures since 1990; Henan, Hunan, Xingjiang and Guangdong have theirs since 1984, while Zhejiang and Jilin have theirs since 1987 and 1988, respectively. Those provinces (Inner Mongolia, Heilongjiang, Shanghai, Shandong, Hainan, Sichuan and Tibet) with missing depreciation figures for 1995 can be estimated by taking the average of the 1994 and 1996 figures. The national depreciation data are obtained by summing up the provincial data.

Population and schooling data are obtained mainly from the *1990 Population Census of the People's Republic of China* (1990 Census) and the *Tabulation of the 2000 Population Census of the People's Republic of China* (2000 Census). In the construction of human capital, data on the annual graduates of the six schooling levels (Higher Education, Specialized Secondary, Vocational Secondary, Senior Secondary, Junior Secondary and Primary) are obtained from the 1986 - 2002 issues of SYC. Table 5-1 of the 1990 Census provides the schooling population of all ages. The same figures for 2000 can be found in Table 5-1 of the 2000 Census. The provincial mortality rates for all ages are obtained from CSDM (p. 1). The total death population aging 15-64 of different schooling levels in 1990 are obtained from Table 10-13 of the 1990 Census. The migration population of different levels of schooling in each province is given in Tables 11-1 and 11-2 of the 1990 Census. The migration figures of Senior Secondary in 2000 can be located from Table 7-6b of the 2000 Census. The total number of persons migrated to various provinces in 2000 are found in Table 7-3 of the 2000 Census. Since Tibet's migration figures are not available, its migration adjustment on human capital figures is not performed.

There was a change of classification in the level of education between 2003 and 2004 in the China data and the classification since 2004 only showed four levels of education, and the transformation is shown in Li (2009, Appendix). Following the inventory approach in Wang and Yao (2003) and Liu and Li (2006), the data series for the human capital variable used in this paper, similarly adjusted by the number of migration and death, has been revised and updated to 2008.

Appendix Table A1 Technical Efficiency Based on Fully Nonparametric Estimation (1985-2008)

	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	Mean
Beijing	0.8479	0.8392	0.8005	0.7274	0.6696	0.6338	0.5663	0.5597	0.6106	0.6262	0.6982	0.7906	0.8666	0.8720	0.9303	0.8131	0.8413	0.8992	0.8897	0.8733	0.8804	0.9522	0.9876	0.9954	0.7988
Tianjin	0.8586	0.8560	0.8505	0.8493	0.8395	0.8221	0.7956	0.7806	0.7891	0.8085	0.8074	0.8029	0.8170	0.8446	0.9722	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9231	1.0000	0.8924
Heibei	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9958	0.9773	0.9564	0.9275	0.8835	0.8701	0.8951	0.9794
Shanxi	0.8688	0.8406	0.8286	0.8300	0.8340	0.8430	0.8469	0.8511	0.8508	0.8538	0.8535	0.8562	0.8535	0.8344	0.8497	0.8386	0.8435	0.8433	0.8545	0.8592	0.8601	0.8640	0.8442	0.8455	0.8478
Inner Mongolia	1.0000	1.0000	1.0000	0.9788	0.9896	0.9820	0.9323	0.9211	0.9067	0.9091	0.9059	0.9100	0.9191	0.9213	0.9116	0.9269	0.9139	0.9184	0.9310	0.9482	0.9838	1.0000	1.0000	1.0000	0.9504
Liaoning	0.7335	0.6958	0.6569	0.6173	0.5827	0.5648	0.5714	0.5752	0.5933	0.5905	0.6039	0.6184	0.6648	0.6852	0.6626	0.6873	0.6879	0.7061	0.7467	0.8043	0.8160	0.8350	0.9006	0.9227	0.6885
Jilin	0.9447	0.9857	0.9869	0.8965	0.8687	0.8639	0.8354	0.7872	0.7997	0.8051	0.8114	0.8613	0.9170	0.9004	0.9552	0.9927	0.9958	0.9784	0.9979	0.9516	0.9782	0.9925	0.9635	0.8971	0.9153
Heilongjiang	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Shanghai	0.9212	0.9149	0.9235	0.9358	0.9202	0.9285	0.9140	0.9171	0.9828	0.9994	1.0000	1.0000	1.0000	1.0000	0.9507	0.8635	0.9056	1.0000	0.9917	1.0000	1.0000	1.0000	0.9689	0.9416	0.9575
Jiangsu	0.9013	0.8880	0.8808	0.8827	0.8873	0.9026	0.9168	0.9292	0.9469	0.9561	0.9667	0.9802	0.9955	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9598
Zhejiang	0.9842	0.9916	0.9936	0.9926	0.9988	0.9993	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9814	0.9734	0.9993	0.9885	1.0000	1.0000	1.0000	1.0000	1.0000	0.9995	0.9947	0.9933	0.9954
Anhui	0.9817	0.9837	0.9792	0.9729	0.9766	0.9677	0.9675	0.9884	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9924
Fujian	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Jiangxi	0.9640	0.9585	0.9546	0.9529	0.9469	0.9552	0.9658	0.9513	0.9457	0.9577	0.9777	0.9618	0.9484	0.9395	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9733	0.9680	0.9807	0.9344	0.9682
Shandong	0.9213	0.9271	0.9183	0.9021	0.9065	0.9105	0.8884	0.8826	0.8839	0.8922	0.9012	0.9286	0.9341	0.9319	0.9461	0.9337	0.9330	0.9449	0.9638	0.9850	1.0000	1.0000	0.9773	0.9642	0.9324
Henan	0.8787	0.8722	0.8614	0.8512	0.8618	0.8513	0.8312	0.8203	0.8146	0.8214	0.8275	0.8227	0.8176	0.8455	0.8838	0.8669	0.8816	0.8860	0.8906	0.8983	0.8858	0.8991	0.9249	0.9049	0.8625
Hubei	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9929	0.9997
Hunan	1.0000	1.0000	1.0000	0.9988	0.9970	0.9879	0.9784	0.9745	0.9800	0.9882	0.9965	1.0000	1.0000	1.0000	1.0000	1.0000	0.9834	0.9894	0.9943	1.0000	1.0000	1.0000	1.0000	1.0000	0.9945
Guangdong	0.8848	0.9167	0.9532	0.9693	0.9591	0.9471	0.9416	0.9518	0.9702	0.9911	1.0000	1.0000	1.0000	1.0000	1.0000	0.9967	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9784
Guangxi	0.8865	0.8853	0.8840	0.8837	0.8871	0.8936	0.8935	0.8910	0.8938	0.9071	0.9134	0.9117	0.9101	0.9134	0.9066	0.9066	0.9134	0.9162	0.9184	0.9253	0.9201	0.9131	0.9029	0.8990	0.9032
Hainan	0.8499	0.8485	0.8551	0.8615	0.8585	0.8533	0.8687	0.8568	0.8730	0.8642	0.8660	0.8853	0.9028	0.9163	0.7884	0.8490	0.7945	0.8087	0.8530	0.9062	0.8895	0.8828	0.9637	0.9375	0.8681
Sichuan	1.0000	1.0000	1.0000	0.9992	0.9992	0.9971	0.9956	0.9973	0.9926	0.9955	1.0000	0.9968	0.9971	0.9936	1.0000	0.9906	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9934	0.9950	0.9976
Guizhou	0.9781	0.9771	0.9661	0.9468	0.9225	0.9084	0.9039	0.9071	0.9121	0.9133	0.9229	0.9315	0.9084	0.8936	0.9098	0.9516	0.9045	0.9045	0.9044	0.9044	0.8965	0.8778	0.8539	0.8702	0.9154
Yunnan	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9910	0.9905	0.9697	0.9589	0.9392	0.9157	0.8997	0.8850	0.8732	0.8855	0.9014	0.9671
Tibet	1.0000	0.9990	0.9986	0.9995	1.0000	1.0000	1.0000	1.0000	0.9996	0.9992	0.9991	0.9992	0.9993	0.9991	0.9991	0.9998	1.0000	1.0000	1.0000	0.9893	0.9900	0.9898	0.9958	0.9639	0.9967
Shaanxi	0.8563	0.8481	0.8462	0.8488	0.8462	0.8411	0.8335	0.8281	0.8251	0.8254	0.8264	0.8287	0.8279	0.8313	0.8472	0.8486	0.8759	0.8685	0.8790	0.8743	0.8691	0.8326	0.7806	0.7817	0.8404
Gansu	0.9052	0.9111	0.9063	0.9133	0.9229	0.9406	0.9464	0.9368	0.9676	0.9753	0.9832	0.9880	0.9930	0.9824	0.8825	0.8850	0.8722	0.9073	0.8857	0.8920	0.9233	0.9462	0.9617	0.9162	0.9310
Qinghai	0.9052	0.9074	0.8912	0.8665	0.8559	0.8281	0.8035	0.7809	0.6627	0.6640	0.6661	0.6762	0.6865	0.6789	0.7352	0.7381	0.7375	0.7314	0.7190	0.6833	0.6929	0.7483	0.7699	0.7279	0.7565
Ningxia	0.9861	0.9837	0.9419	0.8692	0.8157	0.7670	0.7183	0.6906	0.6659	0.6555	0.6693	0.6795	0.7206	0.7101	0.7464	0.7484	0.7245	0.7188	0.7160	0.7117	0.7181	0.6938	0.7168	0.7719	0.7558
Xinjiang	0.9248	0.9356	0.8995	0.8572	0.8334	0.8433	0.8003	0.7832	0.7709	0.7569	0.7435	0.7515	0.7594	0.8320	0.9171	0.9866	0.9847	0.9834	0.9822	0.9641	0.9581	0.9359	0.9046	0.8679	0.8740
Mean	0.9328	0.9322	0.9259	0.9134	0.9060	0.9011	0.8905	0.8854	0.8879	0.8919	0.8980	0.9060	0.9140	0.9163	0.9261	0.9261	0.9251	0.9313	0.9337	0.9342	0.9349	0.9362	0.9355	0.9307	0.9173