Exploring the Sources of Labor Productivity Growth and Convergence among State-Owned Forestry Enterprises in Northeast China

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Abstract

The state-owned forestry enterprises (SOFEs) are important producers of forest products in China, and their competitiveness depends largely on their labor productivity (LP). This article is the first to investigate the sources of LP growth and the convergence patterns of SOFEs in northeast China. Based on panel data from 87 SOFEs in northeast China from 2006 to 2018, this article has used the Cobb-Douglas production function to analyze the sources of LP growth, using three convergent methods to explore convergence patterns. The results show that there is a positive correlation between LP and an SOFE's ability to compete, and that both total factor productivity and capital-to-labor ratio significantly contribute to LP growth in all SOFEs of northeast China; however, the role of the quantity of labor was negative. On the whole, all SOFEs did not have σ-convergence in LP growth, but an absolute and a conditional β-convergence. Although the LP divergence between SOFEs in northeast China has not been narrowed, there has been a ''catch-up effect'' in LP growth. These results can help people understand the laws pertaining to LP growth among forest enterprises and also how they may reduce production costs, improving market competitiveness among forest products.

Productivity is an important factor in the competitiveness of the forest industry (Duc et al. 2009). In the short term, the competitiveness of the forest industry is affected by costs of inputs, but in the long term, productivity growth determines competitiveness (Li et al. 2008). Because of the globalization of trade, domestic and foreign markets of forest products such as wastepaper (Shang et al. 2020) have become increasingly integrated. The forestry enterprises in China urgently need to improve international market competitiveness by improving productivity.

Compared with total-factor productivity (TFP), labor productivity (LP) of forestry enterprises denotes single-factor productivity, which refers to the ratio of the outputs of laborers and the corresponding labor consumption. It can also reflect the competitiveness level of forestry enterprises. The state-owned forestry enterprises (SOFEs) are important producers of forest products in China, and the level of their competitiveness depends on LP growth in the long run. Regarding LP, there are two important questions which concern the sources of LP growth and the comparison of productivity performance of SOFEs. Regarding the latter, it is necessary to answer whether or not less productive enterprises can catch up to more productive ones, and whether or not the divergence of LP within enterprises has shrunk.

Literature Review

Most of the existing studies on the sources of LP growth were at the regional or industry level.

One type of study is known as the nonparametric technique, which uses the Malmquist productivity index, data envelopment analysis (DEA), and structural decomposition analysis (SDA). Based on panel data from Spanish regions during 1965 to 1995, Salinas-Jimenez (2003) used the Malmquist productivity indices to distinguish LP growth in terms of technological change, efficiency gain, and

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Forest Prod. J. 70(3):249–255.
doi:10.13073/FPJ-D-19-00024

capital accumulation; this study found that the main driving forces of LP growth were capital accumulation and technological progress. Using panel data from 20 Italian regions between 1982 and 1985, Piacentino and Vassallo (2011) used DEA to explore the sources of LP growth, finding that efficiency change, technological progress, and capital deepening promoted LP growth. Based on input–output tables in China from 1987 to 2005, Yang and Lahr (2010) used SDA to break down the sources of changes in LP growth into six partial factors; they ultimately found that labor saving is a dominant cause of productivity growth.

The other type of study is the parametric method, which mainly refers to the production function. Using annual time-series data from Malaysia during 1972 to 2005, Wye (2012) built the Cobb-Douglas production function using the Solow residual approach in order to determine the sources of LP growth by economic sector, and found that the LP growth of major economic sectors in Malaysia was significantly affected by both the capital-to-labor ratio and quantity of labor, but less affected by TFP. Based on a panel of 70 countries during 1989 to 2011, Solarin (2016) used the transcendental production function to analyze the sources of LP and found that military burden has a negative influence on LP.

Most of the existing studies on productivity growth and convergence are at the regional level. Based on a panel of 29 regions in China during 1985 to 2000, McErlean and Wu (2003) tested regional agricultural LP convergence in China and found that agricultural LP diverged from 1985 to 1992, but converged between 1992 and 2000. Drawing from 1,263 regional economies of the European Union from 1991 to 2007, Martino (2015) investigated LP convergence and found that there was a clear process of convergence in financial and business-related market services. Based on a panel of 31 provinces in China during 1999 to 2014, Li and Zhang (2016) used absolute β-convergence and conditional β-convergence to test China's industrial LP convergence; they found that China's overall industrial LP presented absolute β-convergence characteristics, while four regions in China showed absolute convergent characteristics. Using service sector data for 95 countries from 1975 to 2012, Kinfemichael and Morshed (2019a) used absolute β-convergence to analyze the convergence of LP in the service sector and found that there was absolute β-convergence in LP therein. Based on data from the United States from 1987 to 2015, Kinfemichael and Morshed (2019b) used absolute β-convergence to test the convergence of LP, finding that manufacturing has the highest rate of convergence and was the primary driver of convergence during 1987 to 1997. The methods used by the above scholars were σ-convergence, absolute β-convergence, and conditional β-convergence, which are known as the classical approaches to convergence, according to Sala-i-Martin (1996a, 1996b).

Most of the existing studies about forestry productivity involved TFP and eco-efficiency. Based on a panel of 135 key SOFEs in China during 2001 to 2011, Yang et al. (2016) used Malmquist–DEA to measure TFP and found that TFP variation was positively affected by technological progress, but negatively affected by scale efficiency. Drawing on data from eight regional pulp and paper industries in the United States and Canada from 1971 to 2005, Hussain and Bernard (2017) investigated the presence of TFP convergence and found that it was indeed present. Li et al. (2008) and Lee et al. (2011) also used the Malmquist productivity index to analyze productivity changes in the forest products industry. Based on a panel of 87 SOFEs in China from 2003 to 2016, Ning et al. (2018) used a slacks-based measure of DEA model to measure eco-efficiency and found that low eco-efficiency among enterprises was caused by low pure-technical efficiency.

To date, although there has been significant research into TFP and the eco-efficiency of forestry enterprises, very few studies have focused on their LP. To fill this gap in existing research, this study first explores the sources of LP growth, and subsequently investigates whether convergence in LP exists in the SOFEs of northeast China.

Method

Cobb-Douglas production function

According to research from Cobb and Douglas (1928) and Solow (1957), a Cobb-Douglas production function (C-D function) with a Solow residual approach was constructed. Equation 1 illustrates this:

$$Y = f(K, L, t) = A(t)K^{\gamma_1}L^{\gamma_2} = A_0 e^{\delta t}K^{\gamma_1}L^{\gamma_2} \tag{1}$$

where Y is the output of SOFE; K is capital; L is labor; $A(t) = A_0 e^{\delta t}$, which represents neutral technical change; A_0 represents technical change; t = 1,..., 13 (represents 2006,..., 2018); and γ_1 and γ_2 are the marginal output elasticity coefficients of capital and labor inputs respectively. If $\gamma_1 + \gamma_2 = 1$, it denotes constants to scale; if $\gamma_1 + \gamma_2 < 1$, it denotes diminishing returns to scale; if $\gamma_1 + \gamma_2 > 1$, it denotes increasing returns to scale.

Taking natural logarithms for both sides of Equation1, this equation can be transformed as:

$$\ln(Y) = \ln A_0 + \delta t + \gamma_1 \ln(K) + \gamma_2 \ln L \tag{2}$$

and when ln$L$ is subtracted from both sides of Equation 2, Equation 3 illustrates the result of this process.

$$\ln(Y/L) = \ln A_0 + \gamma_1 \ln(K/L) + (\gamma_1 + \gamma_2 - 1)\ln L + \delta t \tag{3}$$

Equation 3 is the natural logarithmic form of the C-D function. After regression analysis on the equation, we can obtain the marginal LP elasticity coefficients of capital-to-labor ratio (γ_1) and labor ($\gamma_1 + \gamma_2 - 1$). Assuming "$y = Y/L$" represents LP and "$k = K/L$" represents the capital-to-labor ratio, Equation 3 could become Equation 4:

$$\ln y = \ln A_0 + \gamma_1 \ln k + (\gamma_1 + \gamma_2 - 1)\ln L + \delta t \tag{4}$$

Differentiating Equation 4 with respect to t, we get the LP growth equation:

$$\frac{\Delta y}{y} = \gamma_1 \frac{\Delta k}{k} + (\gamma_1 + \gamma_2 - 1)\frac{\Delta L}{L} + \delta \tag{5}$$

In Equation 5, the coefficients of γ_1 and $(\gamma_1 + \gamma_2 - 1)$ are multiplied by the average growth of k and L to measure the contribution of the variables to the LP growth. This also means that LP growth is primarily affected by the capital-to-labor ratio, quantity of labor, and technical change.

The component denoted by δ is calculated by the Solow residual, Equation 6. And it is also expressed as ΔTFP/TFP.

$$\delta = \frac{\Delta \mathrm{TFP}}{\mathrm{TFP}} = \frac{\Delta y}{y} - \gamma_1 \frac{\Delta k}{k} - (\gamma_1 + \gamma_2 - 1)\frac{\Delta L}{L} \tag{6}$$

In the above equation (Eq. 6), the Solow residual (δ) is calculated by subtracting the portions of growth attributed by capital-to-labor ratio and labor from LP growth. In fact, the Solow residual can represent contributions from TFP, which may be caused by a higher quality of physical inputs, human capital improvement, technological progress, technical efficiency, institutional innovation, or other factors (Wye 2012).

In order to compare the contribution of capital-to-labor ratio, labor, and TFP to LP growth, we have measured the three contribution rate (CR) indicators as shown in Equation 7.

$$\mathrm{CR}_k = \frac{\gamma_1 \Delta k/k}{\Delta y/y} \times 100\%$$

$$\mathrm{CR}_L = \frac{(\gamma_1 + \gamma_2 - 1)\Delta L/L}{\Delta y/y} \times 100\%$$

$$\mathrm{CR}_{\mathrm{TFP}} = \frac{\delta}{\Delta y/y} \times 100\% \tag{7}$$

Perpetual inventory method

The perpetual inventory method (PIM) was frequently used to estimate the capital stocks. The steps of using PIM included calculating average growth rate of fixed-asset investment, determining the depreciation rate of fixed assets, estimating the capital stock in the base period, and calculating the capital stock per year (Dan 2008, Berlemann and Wesselhöft 2014, Chen 2014).

Firstly, this article uses the average growth rate of fixed-asset investment of one SOFE during 2006 to 2018 to measure its average growth rate of fixed-asset investment.

Secondly, according to Zhang and Ning's (2018) research, the depreciation rate of forestry-specific fixed-asset investment was about 5.5 percent, so that δ is equal to 5.5 percent in this study.

Thirdly, according to Dan's (2008) and Chen's (2014) research, this paper uses Equation 8 to estimate the capital stock in the base period.

$$K_{i,2006} = \frac{I_{i,2006}}{(r_i + \delta)} \tag{8}$$

where $K_{i,2006}$ is the capital stock of SOFE i in 2006, $I_{i,2006}$ is the fixed-asset investment of SOFE i in 2006, and r_i is the average growth rate of the investment of SOFE i during 2006 to 2018.

Finally, the capital stock of SOFE i in year t is calculated (see Eq. 9).

$$K_{i,t} = K_{i,t-1}(1-\delta) + I_{i,t} \tag{9}$$

where $K_{i,t}$ is the capital stock of SOFE i in t year, $K_{i,t-1}$ is the capital stock of SOFE i in $t-1$ year, and $I_{i,t}$ is the fixed-asset investment of SOFE i in year t.

Three approaches of convergence

Convergence means that underdeveloped economies will catch up with developed economies through the law of diminishing marginal returns for input factors in the long run, which is an important phenomenon in economic growth theory (Han and Cui 2005). The convergence test methods in existing research mainly include σ-convergence, absolute β-convergence, and conditional β-convergence. In this article, by means of analyzing the coefficient of the variation in LP over time, the σ-convergence test was used to determine whether there is convergence. This was done in order to discover whether the differences among SOFEs have diminished. If there is absolute β-convergence, the LP of SOFEs with slower initial growth rates begin to grow faster, leading all SOFEs to tend toward a common steady state, reflecting a natural catch-up effect. The conditional β-convergence test considers the characteristics of each SOFE, which reflects their situations and how each approaches a different steady-state level.

Based on Sala-i-Martin (1996a, 1996b), Miller and Upadhyay (2002), Zeng and Li (2008), and Wu (2009), σ-convergence, absolute β-convergence, and conditional β-convergence equations are set up as follows:

$$cv_t = \alpha_0 + \alpha_1 t + \varepsilon_t \tag{10}$$

$$g_{i,t+T} = \ln(LP_{i,t+T}/LP_{i,t})/T = \beta_0 + \beta_1 \ln(LP_{i,t}) + \varepsilon_{i,t} \tag{11}$$

$$g_{i,t+T} = \ln(LP_{i,t+T}/LP_{i,t})/T = \gamma_i + \beta_0 + \beta_1 \ln(LP_{i,t}) + \varepsilon_{i,t} \tag{12}$$

where cv_t is the coefficient of a variation in the LP of SOFEs, α_0 and β_0 are constants, α_1 and β_1 are coefficients, t is the time variable, ε_t and $\varepsilon_{i,t}$ is the random error term, $g_{i,t}$ is the average LP growth rate, and γ_i is the intercept reflecting the individual characteristics of the SOFEs. We used the ordinary least squares (OLS) model to perform regression analysis for the σ-convergence test. In Equation 10, if $\alpha_1 < 0$, there is a σ-convergence, which means that the regional difference of the LP diminishes. We used the pooled OLS model to perform regression analysis for the absolute β-convergence test. In Equation 11, if $\beta_1 < 0$, there is an absolute β-convergence, which means that because the growth rate is inversely proportional to the initial rate, there is a catch-up effect. Because the fixed-effect model considers individual characteristics, it is superfluous to add additional control variables (Miller and Upadhyay 2002, Wu 2009). We used the fixed-effect model to perform regression analysis on the conditional β-convergence test. In Equation 12, if $\beta_1 < 0$, there is a conditional β-convergence, which means that each SOFE will move toward their own stable state. In general, there is an absolute β-convergence when there is a σ-convergence, and there is a conditional β-convergence when there is an absolute β-convergence.

Data

SOFEs in northeast China

There are 87 SOFEs in northeast China. On average, there are 344,000 hectares of forest for each SOFE. The SOFEs are divided into five groups: 19 SOFEs are part of the Inner Mongolia Forest Industry Group (IM), 8 are part of the Jilin Forest Industry Group (JL), 10 are part of the Changbai Mountain Forest Industry Group (CBM), 40 are part of the Longjiang Forest Industry Enterprise Group (LJ), and 10 are part of the Greater Khingan Forest Industry Group (GK).

Indicator selection and data sources

This article used input and output data from 87 SOFEs in northeast China from 2006 to 2018. The data come from the

China Forestry Statistical Yearbook (State Forestry Administration of China 2006–2016, National Forestry and Grassland Association [NFGA] 2017), the *China Forestry and Grassland Statistical Yearbook* (NFGA 2018*)*, and the website of the National Bureau of Statistics of China (2020). As a matter of convenience, the 87 SOFEs in northeast China are referred to as ''all'' or ''all SOFEs.''

Capital stock is an input indicator of an SOFE. In order to calculate the capital stocks of the SOFEs, we have taken three steps. Firstly, so as to eliminate the influence of price change, total investments of the SOFEs are divided according to the fixed base-price index. Secondly, according the average ratio of the fixed-asset investment to the forestry total investment in China during 2011 to 2018, we calculated the fixed investment of the SOFEs from their total investment. Finally, the capital stocks of the SOFEs are calculated from fixed-asset investment with the PIM.

Labor is an input indicator of an SOFE. Labor of the SOFEs is calculated as the number of on-the-job workers.

Total output is the only output indicator of an SOFE. For eliminating the influence of price change, the total outputs of the SOFEs are divided by the production price index for forest products.

Both fixed base-price indices for fixed-asset investments and the production price index for forest products are calculated by taking 2006 as the base period. Table 1 shows the descriptive statistics of the indicators.

Results

Comparative analysis of LP growth

As shown in Figure 1, the LP of all SOFEs in northeast China revealed a rising trend from 2006 to 2018. During this period, LP declined only in 2010. One possible reason for this decrease could be the global financial crisis, which had a significant impact on most SOFEs. LP increased from 101.54 million yuan per 1,000 people in 2012 to 125.61 million yuan per 1,000 people in 2013, a growth of 23.70 percent, the fastest year-to-year increase within the period.

Between 2006 and 2018, the average annual LP growth rate for all SOFEs was 8.88 percent. By group, the highest average annual LP growth rate was LJ at 11.33 percent, followed by JL at 8.34 percent, IM at 4.97 percent, CBM at 4.81 percent, and GK at 4.73 percent. The reason for this disparity is that the output value growth rate and the labor descent rate were different among the five SOFE groups.

Figure 2 shows the variable coefficient (CV) change in LP among the five SOFE groups and all SOFEs from 2006 to 2018. On the whole, the CV of the LP of all SOFEs in northeast China revealed a rising trend, which indicates that the LP divergences among all SOFEs had become larger.

The average annual CV growth rate of LP among all SOFEs was 6.11 percent between 2006 and 2018. By comparison, the SOFE groups with positive growth rates were IM (9.22%), JL (5.62%), and LJ (4.89%); the SOFE groups with negative growth rates were CBM (–1.08%) and GK (–0.94%). The results indicate that on the whole, the SOFEs of IM, JL, and LJ—i.e., those with slower initial growth rates—had a slower growth overall, so the LP gap among these three groups had become larger. At the same time, though the SOFEs of CBM and GK had slower initial growth rates but showed a higher overall growth rate, the LP divergences among the two groups had become smaller.

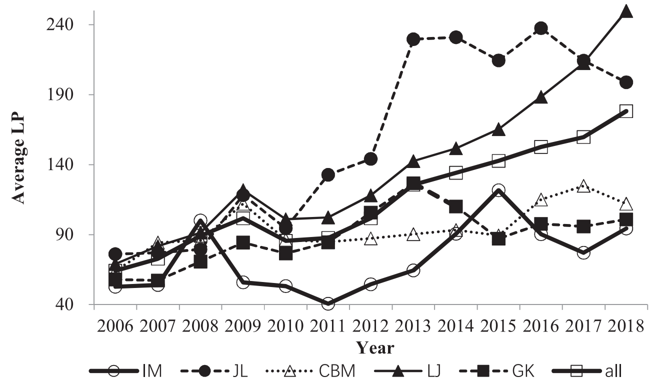

Figure 1.—Average labor productivity (LP) change for the five state-owned forestry enterprise (SOFE) groups and all SOFEs during 2006 to 2018. The average LP of one SOFE group is calculated with the average of the LP of its SOFEs. The average LP of all SOFEs is calculated with average of the LP of the 87 SOFEs. IM = Inner Mongolia Forest Industry Group; JL = Jilin Forest Industry Group; CBM = Changbei Mountain Forest Industry Group; LJ = Longjiang Forest Industry Enterprise Group; GK = Greater Khingan Forest Industry Group.

Sources of LP growth

In order to explore the sources of LP growth among the SOFEs, we have taken three steps. Firstly, based on panel data from 87 SOFEs in northeast China during 2006 to 2018, we used a pooled OLS to estimate Equation 3. Table 2 shows the regression results of the LP growth equation coefficient estimates. It was found that γ_1 was equal to 0.244 and $(\gamma_1 + \gamma_2 - 1)$ was equal to 0.171. Because $(\gamma_1 + \gamma_2)$ was greater than 1, the production of all SOFEs was in a state of increasing returns to scale. Next, the TFP growth rate of every SOFE was calculated with the Solow residual equation (as shown in Eq. 6). Finally, we compared the contribution of the capital-to-labor ratio (k), labor (L) and TFP to LP growth with Equation 5 and Equation 7. Table 3 shows the results of these calculations. By contrast, the contribution rate of TFP to LP growth rate was the highest (53.51%), followed by capital-to-labor ratio (49.49%) and

Table 1.—Descriptive statistics of the input and output indicators.[a]

Item	Indicator	Unit	Observation	Mean	SD	Minimum	Maximum
Input indicators	capital stock	RMB[b] million	1,131	290.61	195.97	23.98	1,071.23
	labor	thousand	1,131	4.38	2.04	0.68	16.27
Output indicators	total output	RMB million	1,131	485.09	337.42	47.12	2,401.13

[a] Calculated based on data from the State Forestry Administration of China (2006–2016), National Forestry and Grassland Administration (2017, 2018) and National Bureau of Statistics of China (2020).

[b] RMB = renminbi.

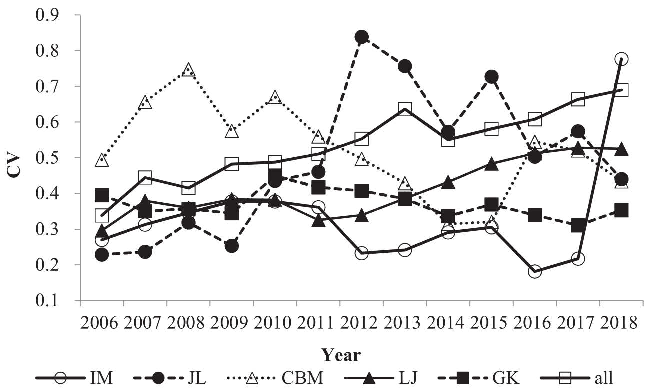

Figure 2.—The coefficient of variation (CV) change of average labor productivity among the five state-owned forestry enterprise (SOFE) groups and all SOFEs during 2006 to 2018. IM = Inner Mongolia Forest Industry Group; JL = Jilin Forest Industry Group; CBM = Changbei Mountain Forest Industry Group; LJ = Longjiang Forest Industry Enterprise Group; GK = Greater Khingan Forest Industry Group.

labor (–3%); this indicates that the LP growth of SOFEs in northeast China was mainly caused by TFP and the capital-to-labor ratio. An interesting result to note is that the contribution rate of labor to LP growth rate was negative. One possible reason for this is that the number of workers in the SOFEs was greater than the optimal number.

Convergence of LP growth

Table 4 shows that the α_1 of all SOFEs was positive and passed the test of significance (presented in the last row). This means that there was no σ-convergence in LP growth between 2006 and 2018, but that there was a ''divergent effect'' among all SOFEs.

As shown in Table 4, the α_1 of the group including CBM and GK was negative, but only α_1 of CBM passed the test of significance. The results indicate that there was α-convergence, as well as the ''catch-up effect'' in CBM, which indicates that the LP divergence of the SOFEs among CBM narrowed. By contrast, the α_1 of JL and LJ was positive and passed the test of significance, which indicates that the LP divergence of the SOFEs among the two groups became wider.

Table 5 indicates that from 2006 to 2018, the β_1 values of all SOFEs and four SOFE groups (without LJ) were negative and passed the test of significance, which means that there was absolute β-convergence in all SOFEs and four SOFE groups. This also means that the SOFEs with slow initial growth rates ended up with larger growth rates on the whole. The β_1 of LJ SOFE group was positive, and did not pass the test of significance, which means that there was no absolute β-convergence in LJ.

Table 6 shows that the β_1 values of all SOFEs and four SOFE groups (without LJ) were also negative and passed the test of significance, which means that there was conditional β-convergence in all SOFEs and four SOFE groups. The conditional β-convergence test indicated that the difference in LP among all SOFEs was due to regional variation in natural conditions and socioeconomic development. If the regional variation was eliminated, LP among all SOFEs and the four SOFE groups would be closer. The β_1 of LJ SOFE group was negative, but did not pass the test of significance, which means that there was no conditional β-convergence in LJ.

Discussion and Conclusion

This article has calculated the LP level and its corresponding average annual growth rate among five SOFE groups and all SOFEs in northeast China during 2006 to 2018. The result was a rising trend across the five groups and all SOFEs, but the LP gap between the five groups remained large. The results from Chen et al. (2017) indicate that production efficiency improvements over time could come from a reform of the SOFEs. Such reforms concern market-oriented changes to encourage SOFEs to use modern enterprise systems, as well as reallocating surplus staff to the other positions. Nelson and Nikolakis (2012) argued that corporatization, or the adoption of more businesslike practices, could improve clarity in business decisions and increase the autonomy of managers, thereby improving the commercial performance of SOFEs. Additionally, the Natural Forest Protection Project was implemented in

Table 2.—Regression results of labor productivity growth equation coefficient estimates.[a]

Regressors	Intercept	ln(*K*/*L*)	ln*L*	*t*	R^2	$F_{3,1127}$
Coefficient	3.181***[b]	0.244***	0.171***	0.026***	0.249	124.550
t value	23.070	6.470	4.960	3.130		

[a] Regression analysis in Equation 3.
[b] * = 10 percent significance level; ** = 5 percent significance level; *** = 1 percent significance level.

Table 3.—Contribution of capital-to-labor ratio (k), labor (L), and total factor productivity (TFP) to labor productivity growth rate.

	$\Delta Y/Y$	k[a]	L[b]	TFP[c]
Contribution	0.121	0.060	−0.004	0.065
Contribution rate (%)	100.00%	49.49%	−3.00%	53.51%

[a] $k = \gamma 1 \times \Delta k/k$. The contribution rate is obtained with Equation 7.
[b] $L = (\gamma 1 + \gamma 2 - 1)\Delta L/L$. The contribution rate is obtained with Equation 7.
[c] $TFP = \Delta TFP/TFP$. The contribution rate is obtained with Equation 7.

Table 4.—Testing σ-convergence of labor productivity growth based on the ordinary least squares model.

SOFE group or all SOFEs[a]	α_0	α_1	R^2	*F*
Inner Mongolia Forest Industry Group	0.276**[b]	0.008[c]	0.041	0.480
Jilin Forest Industry Group	0.270**	0.031**	0.358	6.140
Changbai Mountain Forest Industry Group	0.656***	−0.019**	0.339	5.630
Longjiang Forest Industry Enterprise Group	0.288***	0.018***	0.765	35.800
Greater Khingan Forest Industry Group	0.400***	−0.004	0.159	2.070
All	0.362***	0.025***	0.896	94.830

[a] SOFE = state-owned forestry enterprise.
[b] * = 10 percent significance level; ** = 5 percent significance level; *** = 1 percent significance level.
[c] If α_1 was negative and it passed the significance test, there was a σ-convergence, which meant that the regional difference of the labor productivity diminished.

Table 5.—*Testing absolute β-convergence of labor productivity growth based on the pooled ordinary least squares model.*

SOFE group or all SOFEs[a]	β_0	β_1	R^2	F
Inner Mongolia Forest Industry Group	1.002***[b]	−0.235***	0.435	42.390
Jilin Forest Industry Group	0.614***	−0.118***	0.273	8.260
Changbai Mountain Forest Industry Group	0.637***	−0.137***	0.268	10.250
Longjiang Forest Industry Enterprise Group	0.068	0.008	0.003	0.300
Greater Khingan Forest Industry Group	0.440***	−0.093***	0.223	8.030
All	0.313***	−0.055***	0.057	15.670

[a] SOFE = state-owned forestry enterprise.
[b] * = 10 percent significance level; ** = 5 percent significance level; *** = 1 percent significance level.

1998, after which timber harvesting from SOFEs decreased significantly (Ning et al. 2018). In 2014, the Chinese government began a strict ban on the commercial logging of natural forests in northeast China (Xue et al. 2018). The total output growth rate of the SOFEs, which were highly dependent on timber harvesting, slowed significantly. The LP growth rate followed a similar course. Based on panel data from 87 SOFEs in northeast China from 2006 to 2018, the pooled OLS was used to perform regression analysis on the natural logarithmic form of C-D function and estimate the marginal LP elasticity coefficients of capital-to-labor ratio ($\gamma_1 = 0.244$) and labor ($[\gamma_1 + \gamma_2 - 1] = 0.171$). Because $\gamma_1 + \gamma_2$ was greater than 1, the production of all SOFEs was in a state of increasing returns to scale. After comparing the contribution of capital-to-labor ratio (k), labor (L), and TFP to LP growth, we found that the contribution rate of TFP to LP growth rate was the highest (53.51%), followed by capital-to-labor ratio (49.49%) and labor (–3.00%). This means that the LP growth of SOFEs in northeast China was primarily caused by TFP and capital-to-labor ratio. The increasing capital-to-labor ratio was dependent mainly on physical capital investment, especially on fixed-asset investment. The TFP growth (or productivity) was driven by technical and scale efficiency changes (Li et al. 2008, Lee et al. 2011, Yang et al. 2016). Hall and Jones (1999) argued that the variation in LP across countries was partially caused by differences in both physical capital and educational attainment, which were caused by social infrastructure. Yang et al. (2016) suggested that technical progress—the main driver of growth—along with other inputs could improve the productivity of SOFEs. There are some technological innovations that have been or will be applied in the forest industry that could be used to improve the productivity of forestry enterprises. For example, the new wood-based processing technologies can yield more fiber from smaller-diameter logs across underutilized species (Baldwin 2020).

This article used CVs to compare the LP growth of 87 SOFEs in northeast China, using three convergence test methods to evaluate the convergence conditions from 2006 to 2018. On the whole, the CV of the LP of all SOFEs showed a rising trend. The LP gap between all SOFEs, rather than narrowing, has increased from 2006 to 2018. The convergence analysis results show that on the whole, all SOFEs did not have σ-convergence in LP growth but had absolute β-convergence and conditional β-convergence.

Table 6.—*Testing conditional β-convergence of labor productivity growth based on the fixed effect model.*

SOFE group or all SOFEs[a]	β_0	β_1	R^2	F
Inner Mongolia Forest Industry Group	1.283***[b]	−0.302***[c]	0.649	68.390
Jilin Forest Industry Group	0.797***	−0.158***	0.420	10.840
Changbai Mountain Forest Industry Group	0.943***	−0.209***	0.437	14.740
Longjiang Forest Industry Enterprise Group	0.161*	−0.013	0.006	0.460
Greater Khingan Forest Industry Group	0.816***	−0.182***	0.503	19.200
All	0.692***	−0.141***	0.277	66.390

[a] SOFE = state-owned forestry enterprise.
[b] * = 10 percent significance level; ** = 5 percent significance level; *** = 1 percent significance level.
[c] If β_1 was negative and it passed the significance test, there was conditional β-convergence, which meant that each SOFE would move toward its own stable state.

This means that there was also a ''catch-up effect'' in the LP growth of all SOFEs. These results indicate that there was a natural catch-up effect, and that the LP of SOFEs with slower initial growth grew faster.

Acknowledgment

The research of this article is sponsored by the Fundamental Research Funds of CAF (grant no. CAFYBB2019MB001) and the National Natural Science Foundation of China (grant no. 71603126, 71911530164).

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