Research on the impact of innovation investment on operating efficiency of listed forest product processing companies

Huifang Li and Xinsheng Pang
School of Economics and Management, Beijing Forestry University, Beijing, China

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Abstract

Purpose – The forest products processing industry is a key component of the forestry economy, and the level of companies' operating efficiency directly affects its profitability and market competitiveness.

Design/methodology/approach – In order to deeply study the operation status of forest product processing industry, this paper takes the panel data of 70 listed forest product processing companies from 2015 to 2022 as the basis, and adopts BBC, CCR and DEA-Malmquist models to measure the operating efficiency of these companies. Meanwhile, the Tobit model is applied to deeply explore the impact of innovation input on operating efficiency.

Findings – The results of the paper show that: (1) the overall operating efficiency of listed forest product processing companies performs well, and the improvement of technology level promotes the growth of total factor productivity; (2) innovation input plays a significant positive role in listed forest product processing companies, which positively affects the operating efficiency.

Practical implications – A scientific and reasonable evaluation of the operating efficiency of listed forest product companies is of great practical significance to the development of the forestry industry The study of forest product processing industry is of key significance to the social economy.

Originality/value – This paper explores the improvement of production and operation efficiency of forest products processing enterprises for the purpose of in-depth analysis of the current situation of China's forest products processing enterprises, which is conducive to improving the innovation and operation efficiency of China's forest products processing enterprises, and realizing the high-quality development of China's forest products processing industry.

Keywords Tobit model, DEA Malmquist model, Listed companies engaged in forest product processing

Paper type Research paper

1. Introduction

Growing world demand for wood-processed products (Schons *et al.*, 2020) underscores the importance of strengthening forestry production and improving work efficiency for the sustainable development of the forestry industry. Across the globe, countries exhibit diverse strategies in nurturing innovation within the forest product sector. Developed nations, with their advanced technological infrastructure, have pioneered green technologies and sustainable practices, setting benchmarks in operational efficiency and environmental stewardship. Meanwhile, emerging economies are witnessing an urgent need to harness innovation investments to leapfrog to greener technologies and processes, thereby ensuring their competitive edge and contributing to global sustainability goals. In the forest products processing industry, listed companies, as a representative business form, have garnered

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significant attention for the relationship between innovation input and operating efficiency. China's forestry economic growth is transforming from quantitative expansion to quality enhancement (Ke *et al.*, 2020). Efficiency improvement is crucial for enhancing companies' competitiveness and providing a basis for setting appropriate national forestry policies (Yin *et al.*, 2022). As a typical manufacturing industry, the forest product processing industry relies on substantial production input such as labor, machinery, and equipment (Jiang *et al.*, 2022). Due to resource specificity and production process complexity, improving operating efficiency is often more challenging than in other industries, posing a major problem for forest product processing companies.

Increased innovation capacity of firms leads to qualitative and quantitative enhancements (Stanková *et al.*, 2022; Ryu *et al.*, 2021; Óscar *et al.*, 2009). As the main driver of forestry innovation, forest products processing listed companies in China's forestry economic development play a pivotal role in improving industry efficiency, aiding forestry companies in achieving sustainable development, and contributing positively to ecological protection and economic growth. Operating efficiency is recognized as a key driver of continuous improvement (Lee *et al.*, 2019). In the forest products processing industry, companies must continually develop new products, technologies, and processes to meet market demand and enhance product value. Research and development investment is a necessary condition to achieve these goals. Therefore, studying the relationship between innovation investment and operating efficiency of listed forest products processing companies holds great significance in promoting industry sustainability, enhancing company competitiveness, reducing costs, increasing profits, and creating value for the forest products industry (Van Horne *et al.*, 2006; Välimäki *et al.*, 2004; Lu *et al.*, 2023).

2. Research status

Domestic and foreign research on company business efficiency has yielded fruitful results, which have been widely applied across various industries including manufacturing, finance, industry, transportation, tourism, and others. With the depth of research increasing, a more comprehensive system has gradually emerged (Amornkitvikai and Pholphirul, 2023; Labuschagne *et al.*, 2005; Mavlutova *et al.*, 2023; Sueyoshi *et al.*, 2010; Halkos and Petrou, 2018; Sueyoshi and Wang, 2014; Trinks *et al.*, 2020). Currently, methods for measuring business efficiency mainly include stochastic frontier analysis (SFA) and cost methods among parametric methods, and DEA method, Malmquist productivity index method, hierarchical analysis method, and economic value-added method among non-parametric methods. Regarding the operational performance of forestry companies, most domestic studies rely on the company performance evaluation system issued by the Ministry of Finance of the State. These studies often employ various methods to determine indicator weights to measure a company's operating performance (Wang *et al.*, 2020). For example, some scholars used factor analysis to evaluate the operating performance of 14 Chinese listed forestry companies in 2015, revealing significant variation among them. Additionally, some researchers have developed DEA models based on input-output perspectives to evaluate company performance. Nguyet and Kien (2021) applied E-views software for quantitative analysis of panel data to construct a regression model, identifying the relationship and extent of internal factors' influence on the operating efficiency of steel companies in Vietnam. Lazarevic *et al.* (2022) addressed the operating efficiency of companies producing wooden chairs using selected statistical and DEA methods.

Most studies suggest that innovation promotes improvements in business efficiency, aligning with endogenous growth theory, which emphasizes the increasing role of technological progress in social and economic development. R&D investment emerges as a crucial means to enhance scientific and technological innovation capabilities (Sun, 2021).

Garner (2002), through a study of company R&D investment and performance-related indicators, found that greater attention to R&D investment correlates with higher innovation ability and levels, facilitating faster innovation and promoting company competitiveness and performance. Foreign scholars (Ferreira *et al.*, 2020), through empirical studies of 387 companies in Portugal, found that creativity and innovation ability significantly and positively impact performance, with entrepreneurial orientation moderating this effect. Yang and Chen (2023) concluded that corporate R&D investment significantly enhances corporate value creation. Domestic scholars take 17 home appliance industries as samples, use global principal component analysis to construct a comprehensive evaluation index of innovation ability, and use panel data model to empirically analyze the correlation between this index and company performance, and the results show that company innovation ability has a positive correlation with business performance.

Comprehensive domestic and international literature, there have been many studies focusing on the innovation ability and operating efficiency of companies, but these studies have mainly focused on the fields of industry, insurance, finance and tourism, and relatively few studies have been conducted on forest product processing companies (Hovgaard and Hansen, 2004). Methods for evaluating a company's innovation ability include principal component analysis, factor analysis, hierarchical analysis, and the entropy value method. Methods for assessing operating efficiency include stochastic frontier analysis, the cost method, the DEA method, and the Malmquist productivity index method, with the DEA method being the most commonly used. However, there is a paucity of studies on the relationship between innovation inputs and operating efficiency. Therefore, this study will employ data envelopment analysis to measure the operating efficiency of listed forest product processing companies and analyze their operating efficiency from both horizontal and vertical perspectives. Finally, regression models will be used to examine the impact of innovation inputs on the operating efficiency of China's forest product processing companies, with relevant recommendations proposed from the perspectives of companies, industries, and countries.

3. Evaluation of operating efficiency of forest product processing companies in China

3.1 DEA mamlquist model

Data Envelopment Analysis (DEA) is a commonly used evaluation model for efficiency evaluation. DEA is a widely used evaluation method that integrates operations research, economics, econometrics, statistics and other disciplines. The basic idea is to comprehensively analyze the input and output data of decision-making units to obtain the relevant indicators of the efficiency of each DEA, and then rank the efficiency indicators of all the decision-making units to identify the relatively efficient decision-making units. At the same time, projection methods can be used to identify the causes of non-DEA effectiveness or weak DEA effectiveness. They can also determine the direction and degree of improvement, providing managers with management decision-making information. The DEA approach, which was developed in the 1970s, is based on the mathematical programming algorithm and gives more opportunities to analyze efficiency in forestry sector (Mtynarski and Kaliszewski, 2018; Simar and Wilson, 2007; Lertworasirkul *et al.*, 2003). The DEA model is a static efficiency measure and cannot reflect dynamic changes in efficiency development. The Malmquist indicator decomposes the total efficiency change rate of TFPCH into two components: the EFFCH technology change rate and the TECH technology progress rate. This decomposition is based on the efficiency assessment of the DEA model and reflects the development and changes in efficiency more comprehensively. In this paper, BCC and CCR static models are firstly used to calculate the static operating efficiency of listed companies in forest products processing, and then DEA-Malmquist is used to calculate the dynamic efficiency, which can be decomposed into technological change and technological efficiency change. The Malmquist productivity index measures the change in output-oriented productivity. It is based on the definition of the distance function. Under the technological conditions of the period 't', the output-oriented Malmquist productivity change from period 't' to period 't + 1' is calculated as follows:

$$M_0^t\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = D_0^t\left(x^{t+1}, y^{t+1}\right) / D_0^t\left(x^t, y^t\right) \tag{3-1}$$

Where, D0t(xt,yt) is the distance function, (x_t,y_t) and (x_{t+1},y_{t+1}) are the input-output vectors for periods t and t+1, respectively. Similarly, under the technological conditions of period t+1, the Malmquist productivity change from period t to t+1 is:

$$M_0^{t+1}\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = D_0^{t+1}\left(x^{t+1}, y^{t+1}\right) / D_0^{t+1}\left(x^t, y^t\right) \tag{3-2}$$

Under the condition of maintaining the same scale, total factor productivity can be further decomposed into technological change and technological efficiency change.

$$\begin{aligned} M_0^G\left(x^t, y^t, x^{t+1}, y^{t+1}\right) &= \left[M_0^t\left(x^t, y^t, x^{t+1}, y^{t+1}\right) \times M_0^{t+1}\left(x^t, y^t, x^{t+1}, y^{t+1}\right)\right]^{\frac{1}{2}} \\ &= \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^t(x^t, y^t)} \times \frac{D_0^{t+1}(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \\ &= \frac{D_0^{t+1}\left(x^{t+1}, y^{t+1}\right)}{D_0^t\left(x^t, y^t\right)} \times \left[\frac{D_0^t(x^{t+1}, y^{t+1})}{D_0^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_0^t(x^t, y^t)}{D_0^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} \end{aligned} \tag{3-3}$$

3.2 Data sources and variable selection

According to the industry classification standards issued by the Securities and Futures Commission in 2012, the forest products processing industry can be divided into three categories: paper and paper products, wood processing and wood, bamboo, rattan, palm and grass products, and furniture manufacturing. Currently, there are 161 listed companies in China's forest products processing industry. Listed companies whose raw materials are non-wood materials such as metal or whose finished products are non-wood, non-bamboo, non-rattan, non-palm and non-grass products have been eliminated. In addition, since the disclosure of R&D investment in the annual reports of listed companies began in 2015, the data for the years 2015–2022 were selected for study in this paper. In the data collation, some of the forest product processing companies listed after 2016 have serious data missing problems, so these companies were excluded, and finally 70 forest product processing listed companies were screened. The sources of data include the Cathay Pacific database, Prospective Economy Network, and the annual reports of each company. To ensure that the sample is representative, this study combines existing research results and selects total assets (Stanková *et al.*, 2022; Yang *et al.*, 2016; Wang *et al.*, 2020; Li *et al.*, 2023), operating costs and number of employees as input indicators of a company's operating efficiency. Meanwhile, operating income, net profit and return on net assets are selected as output indicators of operating efficiency to comprehensively reflect the company's main business operation, profitability and investor profitability. The details of the indicators are shown in Table 1.

Total assets, as a key financial indicator of the company, not only reflect the scale and financial status of the company, but also can be used for cross-company comparison of financial strength. Operating costs are a core factor affecting a company's profitability, and high operating costs may adversely affect a company's profitability. The number of employees reflects a company's investment in human capital, which reflects the company's management level and the size of its workforce. Operating income and net profit are important indicators of a company's operating conditions, which are used to assess the profitability and operating efficiency of a company's main business. Return on net assets is a key indicator of the profitability of a company's investors and can be used to assess the level of return on net assets for shareholders.

3.3 Analysis of operating efficiency

3.3.1 Static efficiency analysis. By utilizing the CCR and BCC models to assess the operating efficiency of 70 listed forest product processing companies in China, we obtained the average efficiency of China's forest product processing listed companies from 2015 to 2022, as presented in Table 2:

Overall, none of the companies mentioned have achieved the DEA efficiency level. In terms of average efficiency, the comprehensive technical efficiency, pure technical efficiency, and scale efficiency of China's listed forest product processing companies stand at 0.968, 0.972, and 0.996, respectively. These figures indicate a relatively low level of overall operating efficiency. Sincere Win and Huamao Forestry have relatively good operating efficiency with VRS, CRS and SE close to 1. These values imply that the company's operational efficiency is optimal or close to optimal and that resources are utilized efficiently. A closer look at the comprehensive technical efficiency reveals a significant disparity, ranging from 0.889 to 0.989. This suggests that while certain companies (for example, Yazhen Home Furnishing, Rabbit Baby, etc.) demonstrate higher efficiency in resource utilization, others (such as Zhejiang Yongqiang, etc.) have potential for improvement. Regarding pure technical efficiency, the variation from 0.943 to 1 indicates that some companies achieve high levels of pure technical efficiency, yet others must enhance their technological capabilities to boost efficiency. As for the scale efficiency's technical level, the variation among companies stretches from 0.992 to 0.999, showing that most firms operate with considerable scale efficiency. Companies facing lower scale efficiency should consider optimizing their production scale and reallocating their resources to reach greater scale efficiency. Predominantly engaged in primary processing, the forest product processing industry in China, especially among listed companies, tends to have a relatively short establishment period, lacks experience, and suffers from inadequate scientific management and competitiveness. This results in generally lower overall operational efficiency. Moreover, the efficiency levels vary significantly among enterprises due to differences in scale, establishment time, and product production.

3.3.2 Dynamic efficiency analysis. In the previous study, the relative effectiveness of the operating efficiency of 70 listed forest product processing companies was calculated and analyzed using a DEA-based model. However, both methods are based on static cross-sectional data, i.e., static comparative analyses of the same cross-section. Since the static

Variable type	Variable name	unit	Explanation
Input	Total assets	yuan	Total company assets
	business costs	yuan	Operating costs in the annual report
	Number of employees	Person	Number of active employees in the company
Output	revenues	Yuan	Operating income in the annual report
	return on net assets	%	Net profit as a percentage of average shareholders' equity
	net profit	yuan	Total profit – income tax expense

Source(s): Authors own work

Table 1.
Evaluation indicator system for Company's operating efficiency

Company identification	Comprehensive technical efficiency(crs)	Pure technical efficiency (vrs)	Scale efficiency (se)
Kangxin New Material	0.974	0.978	0.996
Daya Sanxiang	0.954	0.954	1
Rabbit Baby	0.978	0.981	0.997
Fenglin Group	0.951	0.953	0.998
Del Future	0.946	0.948	0.998
Yongan Forestry	0.946	0.950	0.996
Zhejiang Yongqiang	0.889	0.890	0.999
Sofia	0.969	0.983	0.986
Xilinmen	0.943	0.943	0.999
Yongyi	0.961	0.970	0.991
HaoLaiKe	0.974	0.975	0.999
Qumei Home Furnishing	0.980	0.981	0.999
Gujia Home	0.987	0.993	0.994
Yazhen Home Furnishing	0.989	0.995	0.994
Jiangshan Opie	0.950	0.951	0.999
Qingshan Paper	0.886	0.889	0.997
Meiliyun	0.927	0.930	0.997
Minfeng Special Paper	0.931	0.936	0.995
Huatai	0.921	0.922	0.998
Chenming Paper	0.970	0.971	0.999
Hengfeng Paper	0.936	0.939	0.997
Mountain Eagle International	0.896	0.917	0.978
Guanhao Hi-Tech	0.944	0.946	0.998
Yueyang Forest Paper	0.902	0.903	1
Bohui Paper	0.937	0.938	1
Kane	0.961	0.964	0.997
Jingxing Paper	0.964	0.965	0.998
Sun Paper	0.966	0.974	0.992
Hexing Packaging	0.968	0.971	0.998
Meiyingsen	0.918	0.918	0.999
Zhongshun Jielou	0.972	0.973	0.999
Qifeng New Material	0.939	0.941	0.998
Shunhao	0.936	0.939	0.998
Xin Tonglian	0.961	0.969	0.992
Global Printing	0.973	0.978	0.995
Yutong Technology	0.913	0.932	0.980
Rongsheng Environmental Protection	0.983	0.986	0.997
Yangzi Flooring	0.983	0.988	0.995
Sincere Win	0.999	1	0.999
Fudeli	0.994	0.997	0.997
Jinsheng Environmental Protection	0.979	0.984	0.995
Feiyu Bamboo	0.989	0.993	0.996
Hunan Bamboo	0.993	0.996	0.997
Huamao Forestry	0.999	1	0.999
Oasis Source	0.988	0.997	0.992
Zijiu Culture	0.996	0.998	0.998
Huiyang	0.994	0.999	0.994
Natural Technology	0.991	0.996	0.994
Zhejiang Dingbang	0.995	0.998	0.997
Yichuang Technology	0.997	0.999	0.999
Yimei Medical	0.997	0.999	0.998

(*continued*)

Table 2. Average operating efficiency of listed forest product processing companies in China, 2015–2022

Company identification	Comprehensive technical efficiency(crs)	Pure technical efficiency (vrs)	Scale efficiency (se)
Xingang Packaging	0.997	0.999	0.997
Xingyu Packaging	0.994	0.997	0.997
Lishu	0.977	0.981	0.996
Huawang Technology	0.995	0.998	0.998
Huitong	0.998	0.999	0.998
Wanji Technology	0.991	0.996	0.995
Daddy Baby	0.978	0.986	0.992
Jinchang	0.985	0.990	0.995
Fotech	0.995	0.999	0.996
Kaifeng New Material	0.991	0.993	0.998
Tessinotec	0.982	0.992	0.991
Chuan Shun Paper and Plastic	0.992	0.995	0.997
BaoYi	0.993	0.997	0.997
Wanbang Special Material	0.991	0.995	0.996
Dobin Display	0.992	0.996	0.996
Tianhua New Material	0.996	0.998	0.998
Huayuean	0.994	0.997	0.998
Yishang	0.969	0.973	0.996
Longtai Home	0.993	0.994	0.999
Mean Value	0.968	0.972	0.996

Table 2.

Source(s): Authors own work

efficiency measure is calculated separately for the relative effectiveness of each decision-making unit in each period, when a sample is not on the frontier in two different periods, its static efficiency value may be higher or lower than that of the previous period, i.e., the period is in an upward or a downward period. Relying solely on the static DEA efficiency measure, it is not possible to observe whether the efficiency of each sample is in an upward or downward state in different periods. At this point, it is necessary to use the Malmquist Total Factor Productivity Change Index (TFPCI) to calculate and analyze the changes in the operating efficiency of each sample in different time series. The Malmquist TFPCI can be further decomposed as follows:

$$\begin{aligned}\text{Total Factor Productivity Change (TFP)} &= \text{Technology Change (TC)} \times \\ &\quad \text{Technical Efficiency Change(TEC)}\end{aligned} \tag{3-4}$$

$$\begin{aligned}\text{Technical Efficiency Change (TEC)} &= \text{Pure technical efficiency change (TE)} \times \\ &\quad \text{Scale efficiency change (SE)}\end{aligned} \tag{3-5}$$

As can be seen from Table 3, the total factor productivity of the 70 listed forest product processing companies is 1.002 in 2015–2022, which indicates a 2% improvement in total factor productivity in 2022 compared to 2015. Among them, technological progress improves by 2%, and technical efficiency as a whole remains unchanged, with technological progress being the main driving force behind the increase in total factor productivity. During the period 2021–2022, total factor productivity reaches its lowest value, falling by 3%, which is caused by a 6% decline in the level of technology even though technological efficiency improves by 3%. It is still not enough to compensate for the fall in total factor productivity caused by the fall in the level of technology. A detailed analysis of the changes in technical efficiency shows a 6% decline during 2015–2022 only during 2019–2020, with most of the time in an upward phase, caused by a 3% decline in both pure technical efficiency and scale efficiency. On the whole, the growth rates of the above five input-output factors as well as the growth rate of total factor productivity are very close to 1, indicating that these 70 listed forest product processing companies have basically maintained a relatively stable growth state during these eight years without any obvious fluctuations. In terms of changes in technical efficiency, there are more years of growth than years of decline. The technical efficiency change can be decomposed into pure technical efficiency change and scale efficiency change. In recent years, pure technical efficiency and scale efficiency have been flat overall, resulting in flat technical efficiency change. In terms of annual changes, movements in the Malmquist productivity index, technical progress and technical efficiency have been uneven between years.

Table 4 presents the results of innovation-driven efficiency and the mean value of the Malmquist Index for the 70 sample companies. Based on these results, the companies can be divided into three echelons, with innovation-driven efficiency and the Malmquist Index equal to 1 and 0.998, respectively. The first echelon contains ten listed companies such as Huatai, Hexing Packaging, Sun Paper, etc., and more than 50% of the listed companies' operating efficiency has been in the state of growth during the eight years, of which Huatai is in the first place, compared with the optimal operating efficiency. Most of the companies in the first echelon started earlier and mainly paper industry, production and operation experience, with good operating ability, the development trend of long-term good. The second echelon contains 25 companies such as Futai technology, Tesi Nuocai, Oasis source, the third echelon of the home furnishing industry, our country's home furnishing industry started late, the development of a short history, fewer years on the market, at a lower level of operating efficiency, the technical level of change needs to be improved, there is a larger space for development, and how to further exploit the advantages of the resources has also become a problem that should be considered by the company to enhance the efficiency of creating and operating. Comprehensive analysis of the above can be found, the vast majority of the sample company Malmquist index is greater than 1, which indicates that from the overall point of view of China's forest products processing listed companies in the business development of the long-term trend towards good. China's forest product processing companies should pay full attention to the development of the current situation, adjust the industrial structure, effectively solve the supply shortage, rising costs and other problems, to improve their own strength, to establish industry advantages.

4. Factors affecting the operating efficiency of forest product processing listed companies

4.1 Tobit model construction

The Tobit model is an economic econometric model proposed by American economist Tobin in 1958 to explore the demand for durable consumer goods. It estimates the functional

Year	Technical efficiency change	Technical change	Pure technical efficiency change	Scale efficiency change	Total factor productivity change
2015–2016	1.002	1.005	1	1.002	1.007
2016–2017	1.001	1.013	1.001	1	1.015
2017–2018	1	0.998	0.999	1.001	0.998
2018–2019	1.001	0.998	1.001	1	0.999
2019–2020	0.994	1.003	0.997	0.997	0.997
2020–2021	1.001	1.005	1	1	1.005
2021–2022	1.003	0.994	1.001	1.002	0.997
Mean Value	1	1.002	1	1	1.002

Source(s): Authors own work

Table 3. Average efficiency of listed forest product processing companies, 2015–2022

Company identification	Technical efficiency change	Technical change	Pure technical efficiency change	Scale efficiency change	Total factor productivity change	Technical efficiency change
Huatai	1.017	1.028	1.010	1.006	1.046	First grade
Bohui Paper	1.011	1.026	1.011	1	1.038	First grade
Hexing Packaging	1.012	1.025	1.011	1.001	1.038	First grade
Sun Paper	1	1.031	1	1	1.031	First grade
Jingxing Paper	1.011	1.014	1.011	1	1.027	First grade
Rabbit Baby	1	1.020	1	1	1.020	First grade
Chenming Paper	1	1.015	1	1	1.015	First grade
Yueyang Forest Paper	1.015	0.999	1.015	1	1.013	First grade
Yongan Forestry	1.009	1.001	1.008	1	1.010	First grade
Gujia Home	1	1.008	1	1	1.008	First grade
Global Printing	1.003	1.005	1.003	1	1.008	First grade
Mountain Eagle International	1.001	1.004	0.998	1.005	1.005	First grade
Guanhao Hi-Tech	1.005	0.999	1.005	1	1.004	First grade
Rongsheng Environmental Protection	1	1.003	1	1	1.004	First grade
Zhongshun Jielou	1.003	1	1.003	1	1.003	First grade
Minfeng Special Paper	1.001	1.002	1.001	1	1.003	First grade
Qingshan Paper	1.004	0.999	1.004	1	1.003	First grade
Qifeng New Material	0.999	1.004	0.995	1.004	1.003	First grade
ChengWin	1	1.002	1	1	1.003	First grade
BaoYi	1	1.001	1	1	1.001	First grade
Kai Feng New Material	1.001	1.001	1.001	1	1.001	First grade
Kane	1	1.001	0.999	1	1.001	First grade
Huamao Forestry	1	1.001	1	1	1.001	First grade
Yongyi	1	1.001	0.999	1.001	1.001	First grade
Quan Shun Paper and Plastic	1.001	1	1	1	1.001	First grade
Futai Technology	0.999	1.001	1	1	1	Second grade
Tessinotec	0.999	1.002	0.999	0.999	1	Second grade
Oasis Source	1	1	1	1	1	Second grade
Shunhao	0.998	1.003	0.998	1	1	Second grade
Natural Technology	1	1	1	1	1	Second grade
Zhejiang Dingbang	1	1	1	1	1	Second grade
Yishang	1	1	1.002	0.999	1	Second grade
Daddy Baby	0.999	1.001	1	0.999	1	Second grade

(*continued*)

Table 4.
Malmquist dynamic efficiency results for forest product processing

Company identification	Technical efficiency change	Technical change	Pure technical efficiency change	Scale efficiency change	Total factor productivity change	Technical efficiency change
Zijiu Culture	0.999	1.001	1	1	1	Second grade
Yimei Medical	1	1	1	1	1	Second grade
Fudeli	1	1	1	1	1	Second grade
Huitong	1	1	1	1	1	Second grade
Hing Kong Packaging	1	1	1	1	1	Second grade
Huiyang	1	1	1	1	0.999	Second grade
Xingyu Packaging	1	1	1	1	0.999	Second grade
Huawang Technology	0.999	1	1	0.999	0.999	Second grade
Wanji Technology	0.999	1.001	0.999	0.999	0.999	Second grade
Wanbang Special Material	0.999	1	0.999	1	0.999	Second grade
Lishu	0.998	1.001	0.999	0.999	0.999	Second grade
Zhejiang Yongqiang	1.003	0.996	1.001	1.002	0.999	Second grade
Hunan Bamboo	0.999	1	1	1	0.999	Second grade
Feiyu Bamboo	0.999	1	1	0.999	0.999	Second grade
Tianhua New Material	0.999	1	0.999	0.999	0.999	Second grade
Yichuang Technology	0.999	1	1	0.999	0.999	Second grade
Jinchang	0.999	1	0.999	1	0.999	Second grade
Dobin Display	0.999	1	1	0.999	0.999	Second grade
Qumei Home Furnishing	1.002	0.996	1.002	1	0.998	Third grade
Longtai Home	0.998	1	0.998	1	0.998	Third grade
Xintonglian	0.999	0.999	0.999	1	0.998	Third grade
Yangzi Flooring	0.998	0.999	0.998	1.001	0.998	Third grade
Jinsheng Environmental Protection	0.998	0.999	0.998	1	0.997	Third grade
Huayuean	0.999	0.998	0.999	0.999	0.997	Third grade
Fenglin Group	0.996	1.001	0.996	1	0.996	Third grade

(*continued*)

Table 4.

Company identification	Technical efficiency change	Technical change	Pure technical efficiency change	Scale efficiency change	Total factor productivity change	Technical efficiency change
Yutong Technology	0.997	1	0.989	1.008	0.996	Third grade
Sofia	1.003	0.993	1.002	1	0.996	Third grade
Xilinmen	1.001	0.995	1.001	1	0.996	Third grade
Hengfeng Paper	0.997	0.998	0.997	1	0.995	Third grade
Meiliyun	0.995	1.001	0.988	1.007	0.995	Third grade
HaoLaiKe	1.002	0.993	1.001	1.001	0.995	Third grade
Yazhen Home	0.998	0.996	1	0.999	0.994	Third grade
Kangxin New Material	0.994	1	0.995	0.999	0.994	Third grade
Del Future	0.993	0.997	0.993	1	0.990	Third grade
Meiyingsen	0.995	0.994	0.995	1	0.989	Third grade
Daya Sanxiang	0.991	0.996	0.992	1	0.987	Third grade
Jiangshan Opie	0.993	0.993	0.993	1	0.985	Third grade

Table 4.

Source(s): Authors own work

relationship between the demand for the investigated product and its influencing factors by establishing a series of independent variables, and classifies the investigated product based on these functional relationships. The Tobit model uses restricted dependent variables to test regression, which means that the explanatory variables are observable, while the dependent variables can only be observed under certain restrictions. In the forest product processing industry, the application of the Tobit model provides profound insights into the operational efficiency of enterprises and the factors influencing it (Zou *et al.*, 2022; Chen *et al.*, 2024). Since the efficiency values assessed by the DEA model are confined to the [0,1] interval, using the Tobit model for further analysis can effectively avoid the estimation biases and inconsistencies that might arise from traditional ordinary least squares regression. This is particularly crucial for identifying and explaining the factors that contribute to the differences in efficiency among enterprises within the forest product processing industry.

The general form of Tobit model is as follows:

$$\begin{cases} y_i^* = \beta X_i + \mu_i \\ y_i = y_i^*, y_i^* > 0 \\ y_i = 0, y_i^* \leq 0 \end{cases} \tag{4-1}$$

where, y_i^* is latent dependent variable, yi is the observed dependent variable, x_i is the vector of independent variables, β is the vector of correlation coefficients, and the error term μ_i is independent and obeys a normal distribution: $\mu_i \sim N(0, \sigma^2)$, so $\sim N(y_i^* X_i\beta, \sigma^2)$, which is independent and identically distributed.

In order to study the factors that affect the operating efficiency of China's forest product processing listed companies, this article uses the Tobit model to measure the impact of each factor on operating efficiency. This article uses R&D investment as a key variable to examine its impact on the company's operating efficiency, and selects listing time, equity structure, capital structure, and intangible assets as control variables to make the model more robust. The specific form of the model is as follows:

The Tobit model for the impact of various factors on operating efficiency is:

$$CRS_{it} = \alpha_0 + \alpha_1 RDE_{it} + \alpha_2 TM_{it} + \alpha_3 GQ_{it} + \alpha_4 ZC_{it} + \varepsilon_{it} \tag{4-2}$$

$$VRS_{it} = \beta_0 + \beta_1 RDE_{it} + \beta_2 TM_{it} + \beta_3 GQ_{it} + \beta_4 ZC_{it} + \zeta_{it} \tag{4-3}$$

$$SE_{it} = \delta_0 + \delta_1 RDE_{it} + \delta_2 TM_{it} + \delta_3 GQ_{it} + \delta_4 ZC_{it} + \eta_{it} \tag{4-4}$$

Formula (4–2) ~ formula (4–4), α_0, β_0 and δ0 are intercepts, ε, ζ, η represent residual terms, i represents a certain company, t represents time; CRS represents comprehensive efficiency, VRS represents pure technical efficiency, SE represents scale efficiency. Y represents operating efficiency, which is calculated using the DEA static model in this section. RDE represents innovation input, which is represented by the logarithm of R&D investment amount; TM represents the establishment time of the forest product processing company; GQ represents the equity structure, which is represented by the shareholding ratio of the top ten shareholders; ZC represents the asset-liability ratio, which is used to measure the capital structure of listed companies. The Tobit model indicators are shown in Table 5.

H1. The higher the R&D investment of forest product processing listed companies, the higher the operating efficiency. R&D activities are an important driver of innovation (Yam *et al.*, 2011). It is also an important factor affecting business performance. The higher the R&D investment of forest product processing listed companies, the more resources and energy they will invest in developing new products, technologies, and services, thereby enhancing their competitiveness. High R&D expenses indicate that the company is constantly investing funds and energy to improve its products, technologies, and services to meet customer requirements and expectations, and to prepare for improving the long-term profitability of the company.

H2. The longer the establishment time of forest product processing companies, the higher the operating efficiency. Companies with a long establishment time have richer production and operation experience and accumulate more upstream and downstream social capital than those with a short establishment time, often resulting in higher operating efficiency.

Type of variable	Variable Name	Variable symbols	Calculation method
Explained Variables	Operating Efficiency of Listed Forestry Companies	Y	Efficiency values measured by DEA
Explanatory Variable	Innovation Input	RED	R&D investment costs in annual report
Control Variables	Listing time	TM	Listed within this year's limit
	Shareholding structure	GQ	Shareholding ratio of top ten shareholders
	Capital Structure	ZC	Asset-liability ratio

Source(s): Authors own work

Table 5. Tobit model indicator system

H3. The equity power structure of a company is a key factor in determining how to protect the interests of shareholders from any potential exploitation by agents. Investors in companies with a fragmented shareholding structure lack sufficient resources and willingness to operate and manage the company with increased difficulty (Ali *et al.*, 2018). The higher the equity concentration of listed companies in forest product processing, the higher the operating efficiency. The higher the concentration of corporate shares, the greater the motivation of major shareholders to participate in corporate decision-making, and the higher the efficiency of corporate decision-making, which is conducive to improving the operating efficiency of the company.

H4. The lower the asset-liability ratio of a listed forest product processing company, the higher its operating efficiency. A low debt-to-asset ratio reflects a strong financial condition and improves operating efficiency (Li *et al.*, 2023). It provides businesses with more investment opportunities, such as expanding business scale, developing new products, and entering new markets. Consequently, this increases revenue, market share, and company value.

When a company's asset-liability ratio is low, it is usually seen as a positive signal, indicating that the company has achieved good results in operations, indicating that the company's financial situation is healthy and does not rely on excessive borrowing to support operations, making it easier to respond to unexpected events.

4.2 Empirical results and analysis of tobit model

This study uses stata16.0 statistical analysis software to carry out Tobit regression analysis on the factors affecting operating efficiency, the explanatory variable operating efficiency is measured by the DEA model, and the output results are between [0, 1], which is truncated data, and the use of the OLS model will lead to biased results, based on the use of the data belongs to the panel data, and the results of the LR test show that there is an individual effect, so the random effect Tobit model was selected for estimation. Therefore, the random effect Tobit model was selected for estimation and the regression results are shown in Table 6:

From the results of LR test, the original hypothesis is strongly rejected, so we believe that there is an individual effect, and the Tobit panel model under the random effect further verifies the reasonableness of the model construction in this paper. From the value of Wald χ^2, it can be concluded that the model passes the test at 1% significance level, indicating that the regression equation constructed by the model is reasonable, and the specific analysis of the indicators of each influence factor is as follows.

(1) R&D investment shows a significant positive relationship with each efficiency and is significant with CRS and VRS at 5% significance level, indicating that R&D investment has a significant positive impact on the operating efficiency of listed companies in forest products processing. R&D investment helps companies to acquire new technology and new products, which in turn promotes the long-term development of the company (Christensen *et al.*, 2018). In the development process of the company, it is necessary to continuously strengthen the research and development of new products to ensure the increase of its production capacity. Investment in technology R&D is the key to improving the level of investment in technology R&D and to increasing the efficiency of investment in technology R&D. However, in the reality of operation, the lack of sufficient attention to innovative R&D often leads to insufficient investment in R&D, which in turn severely restricts the company's development capacity.

Table 6. Tobit regression results of operating efficiency of listed forest products companies

Variables	CRS	VRS	SE
RED	0.00255**	0.00259**	0.0002
	(1.79)	(2.11)	(0.27)
TM	0.00037	0.00045	0.0010
	(1.95)	(1.37)	(73.59)
GQ	0.09464***	0.09777***	0.0078***
	(4.38)	(5.64)	(1.07)
ZC	−0.000349***	−0.00033***	−0.0200***
	(−4.04)	(−3.41)	(−3.21)
_cons	0.8662***	0.88654***	0.9872***
LR	206.34***	188.65***	53.38***
Wald χ^2	77.06***	77.25***	12.6***

Note(s): $*p < 0.05$, $**p < 0.01$, $***p < 0.001$
Source(s): Authors own work

(2) There is no significant effect of the time of establishment and none of the above operating efficiency. As the company's establishment time increases, the accumulated capital and experience also increases, which brings greater advantages to the production and operation of the company. However, the effect of the age of the firm on operating efficiency has been highly debated. Although high efficiency is gradually accumulated over time, companies that are old have difficulties in adapting to the ever-changing environment and increasing competitive pressure, and therefore show disadvantages such as rigid thinking and lagging management concepts in their operations, which cause them to be at a competitive disadvantage and may even lag behind emerging companies. In the long run, as the scale of the company continues to expand, its operating efficiency will first rise and then decline.

(3) Equity concentration has a significant effect on both operating efficiency and its decomposition term. Theoretically, the higher the equity concentration, the more timely the company's decision-making, thus effectively seizing market opportunities and obtaining higher operating efficiency; on the contrary, if the equity concentration is relatively low, the company's shareholders are constrained by each other, which may lead to delayed decision-making and missed market opportunities (Atanasov, 2005).

(4) Gearing ratio shows a significant negative correlation with operating efficiency of listed companies in forest products processing, and all of them are significant at 1% significance level. This indicates that the lower the gearing ratio of listed companies in forest product processing, the better the company's capital status and the higher its operating efficiency. Low gearing ratio can also indicate that the company has more investment opportunities. Compared with firms with high gearing ratios, firms with low gearing ratios have more free cash flow and are therefore more likely to make new investments. These investments include expanding the scale of business, developing new products, and entering new markets. These investments not only increase the revenue and market share of the firm, but also increase the value of the firm.

5. Conclusions and recommendations

5.1 Discussion

In this study, we employed DEA and Tobit models to examine the operational efficiency and its determinants among Chinese forest product processing firms. These models have provided valuable insights into the complex dynamics of operational efficiency within the industry. The DEA model, in particular, offers a robust framework for evaluating relative efficiency among firms, enabling us to identify high performers and understand the efficiency frontier. Despite potential influences from sample selection and external variables, its application allows for a comprehensive analysis of operational practices. Similarly, the Tobit model, with its focus on censored data, is especially suited for examining the intricacies of efficiency determinants in the presence of upper or lower bounds. While assumptions regarding data distribution might impact parameter estimates, the Tobit model's methodological rigor enhances our understanding of the factors influencing operational efficiency. Its application is a testament to the sophisticated analytical approaches available for tackling econometric challenges in efficiency studies.

5.2 Conclusion

This paper uses the panel data of 23 listed forest product processing companies from 2012 to 2021 to measure their operating efficiency by DEA model. The dynamic fluctuation of operating efficiency is analyzed, and a Tobit model is subsequently established to explore the impact of innovation inputs on operating efficiency. The study shows that: (1) The overall operating efficiency of listed forest product processing companies is good without obvious fluctuations, and analyzed from the source of total factor productivity growth, technical efficiency is the power source driving the growth of total factor productivity, and the decline of technological progress plays a reverse role. Within forest product processing companies, those in the paper industry exhibit the highest operating efficiency, followed by wood processing. The furniture manufacturing industry demonstrates the lowest efficiency. (2) The impact of innovation investment on the operating efficiency of listed companies in forest product processing is significantly positive. Innovation investment plays a positive role in the company's operating activities. R&D expenses can improve the quality and technology content of products, make products more competitive, thus improving the productivity of companies and helping the company's operating efficiency. In addition, gearing ratio has a significant negative effect on operating efficiency and time of establishment is positively related to operating efficiency.

5.3 Recommendations

With the development of the global economy, the forest product processing industry, as one of the key manufacturing sectors, plays an indispensable role in China. As a rapidly developing country among developing nations, China's growth patterns in the forest product processing industry can offer valuable insights for other developing countries. According to the results of the above research, in order to improve the operating efficiency of listed companies in forest products processing, enhance the stability of operating efficiency, play a leading role in listed companies in forest products processing, enhance the competitiveness of the company, the following recommendations are put forward: (1) company level:the forest product processing industry in our country currently exhibits a trend towards the lower end, particularly lagging behind developed countries in terms of deep processing. Companies should consider technological advancement and the improvement of total factor productivity as their core strategy, enhancing efficiency through strengthening internal R&D capabilities and adopting cutting-edge technologies. (2) Industry level: China's forest products processing industry in most of the company scale is small, engaged in the primary processing of forest products, lack of competitiveness, due to the lack of technological innovation, deep processing of forest products is not enough companies. Forest products processing companies engaged in furniture manufacturing started late. But there is a greater potential for development, the appearance of design and other aspects of innovation still have more space to increase the furniture manufacturing industry's investment in innovation. Increasing investment in innovation can guide the furniture manufacturing industry to the intelligent direction of transformation. (3) National level: the government should recognize the differences in operating efficiency among forest product processing companies and provide differentiated support for various types of such companies. By increasing research investment and optimizing tax policies, it can significantly promote technological advancement and facilitate industrial upgrading within the industry.

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Corresponding author
Xinsheng Pang can be contacted at: pxinsheng@bjfu.edu.cn