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EFFICIENCY ANALYSIS OF THE CHILEAN SAWMILL INDUSTRY

Wilson Alexander Mejías Caballero[1,♠]

https://orcid.org/0000-0002-3064-6940

Pamela Poblete[1]

https://orcid.org/0009-0008-2046-5709

Janina Gysling[1]

https://orcid.org/0000-0001-8428-8846

Indroneil Ganguly[2]

https://orcid.org/0000-0002-9075-2665

Daniel Sepúlveda Oehninger[3]

https://orcid.org/0000-0002-3129-393X

ABSTRACT

Chile plays a significant role in global sawn wood production, ranking 14th in total roundwood and 10th in coniferous sawn wood production in 2022, contributing significantly to the demand for wood products. In the same year, the country exported wood products worth a remarkable $US 6.682 million of, underscoring its importance in the global wood industry. Despite its prominence, the sector has faced significant including mega forest fires and the COVID-19 pandemic, which have adversely affected its performance. One notable issue is the decline in the number of active sawmill units, with only 61 currently producing sawn wood with structural characteristics. The highlights the pressing need to quantify and optimize efficiency within the industry. To address this, Stochastic Frontier Analysis a valuable mathematical framework for evaluating industry efficiency, was employed. Using a dataset compiled by the Chilean Forestry Institute and applying the Stochastic Frontier Analysis methodology, this research assessed the average efficiency of the Chilean sawmill sector. The analysis, based on two different models, consistently revealed a decline in average efficiency during the pandemic. Furthermore, it identified a longitudinal gradient in the efficiency of sawn wood production, with technical inefficiency decreasing towards the southern regions of the country. However, the study did not find direct evidence of a correlation between productivity and the production scale of sawmills. Instead, cost factors, including raw materials, labor, and supplementary expenses, emerged as critical areas requiring careful attention to improve the overall efficiency of the industry.

Keywords: Chilean sawmill industry, efficiency analysis, sawmill efficiency, sawn wood, lumber production, stochastic frontier analysis.

[1]Instituto Forestal. Departamento de información y economía forestal. Santiago, Chile.
[2]University of Washington. Center for International Trade in Forest Products. Seattle, USA.
[3]Metropolitan University of Technology. Faculty of Natural Sciences, Mathematics and Environment. Department of Mathematics. Santiago, Chile.
♠Corresponding author: w.a.mejias@gmail.com
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INTRODUCTION

Wood plays a critically important role in the global forestry industry, serving as a fundamental resource for a wide range of applications, from construction to furniture and paper production. In the year 2022, global production of roundwood reached 4008,6 million cubic meters, demonstrating the growing global demand (FAO 2023).

According to FAO (Food and Agriculture Organization), Chile stands out as a significant player in global sawn wood production. With a production of 59,8 million cubic meters in the same year, Chile ranks 14th globally in total roundwood production. Furthermore, as a producer of sawn coniferous wood, Chile is positioned 10th globally, distinguishing itself as the leader in South America in this regard during the year 2022 (FAO 2023).

Sawn wood plays an essential role in the global economy, and Chile, with its substantial production and leadership in sawn coniferous wood in South America, plays a prominent role in meeting this global demand.

Forestry and sawmilling sector in Chile

The forestry industry is one of the main economic sectors in the country, with sawmilling being a relevant activity in Chile. The activity is primarily based on the utilization of logs from forest plantations covering an area of 2,3 million hectares, predominantly composed of radiata pine (*Pinus radiata* D.Don) (67,9 %), blue gum (*Eucalyptus globulus* Labill.)(20,8 %), and shining gum (*Eucalyptus nitens* H.Deane & Maiden) (10,3 %) (Álvarez *et al.* 2022b). Notably, the sawmilling industry relies almost exclusively on radiata pine (*Pinus radiata* D.Don), as other species face difficulties in producing sawn wood (Álvarez *et al.* 2022a).

In 2021, the industrial consumption of roundwood reached 43,6 million cubic meters (Álvarez *et al.* 2022b). The sawmilling industry and the pulp industry have the highest consumption of roundwood. The former accounted for 38,1 % of the total volume in 2021, followed by the pulp industry with 36,7 %. To a lesser extent, there is the wood chip industry, accounting for 12,9 %; the panel and veneer industry, accounting for 9 %; and the treated poles and posts industry (Álvarez *et al.* 2022a).

The production of sawn wood in Chile during 2021 reached 8,7 million cubic meters, of which 75 % was destined for the domestic market, while the remaining 25 % was destined for the international market. This production was carried out in 922 sawmills of different production ranges. 55,8 % of the volume of sawn wood was produced in 21 sawmills classified as “large”, meaning they have an annual production capacity equal to or exceeding 100 thousand cubic meters (Álvarez *et al.* 2022b).

Forest product exports in 2022 totalled US$ 6.682 million, equivalent to 12 % of national exports in this year. The three products that have led Chilean forest exports in recent years are bleached pine pulp, bleached eucalyptus pulp, and sawn pine wood in planks, with China (29,2 %) and the United States (25,7 %) being the main destinations (Kahler *et al*. 2023).

The total number of sawmills in Chile in 2021 reached 1.233 units, including operational and non-operational units. Over the past few years, there has been a decrease in active units, dropping from 1056 operational units in 2015 to 922 units in 2021. Furthermore, only 61 of these units produce sawn wood with structural characteristics, therefore less than 7 % of sawmills currently in operation produce this type of materials. (Álvarez *et al*. 2022a). According to the information gathered by Chilean Forestry Institute (INFOR) (Gysling *et al*. 2021), one of the major challenges faced by the sawmilling industry is the supply of quality logs. This situation becomes even more critical due to the loss of forest resources caused by large forest fires that have occurred in recent years. Therefore, it is crucial to focus on improving the efficiency of the sawmilling industry, starting with understanding how this variable is spatially distributed and how it has evolved in recent years.

In Chilean sawmilling operations, efficiency is typically assessed by means of average productivity, quantified as the number of physical production units (cubic meters of wood) per individual engaged in the industry Álvarez *et al*. (2022a). This metric, however, does not consider other contributing factors such as machinery costs, energy expenditures, or other relevant variables. Another definition of efficiency is as the difference between actual production and maximum possible production (Ferrara 2020).

There are numerous techniques used to measure this relationship, with the most important ones being Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) (Núñez *et al*. 2004, Ferrara 2020). DEA and SFA method employ a set of resource variables utilized within a productive process to estimate potential productivity values. In SFA, an explicit functional form for the production frontier must be specified a priori, whereas DEA determines relative efficiency through linear programming without specifying a functional form. While DEA offers flexibility and generalizability by not requiring a detailed production process description, its deterministic nature limits its ability to differentiate between inefficiency and random disturbances affecting efficiency (Corte 2015). The efficiency of the sawmill industry has been modelled extensively using these techniques, with numerous studies applying both the DEA approach (Nyrud and Baardsen 2003, Salehirad and Sowlati 2005) and the SFA approach (Niquidet and Nelson 2010, Ogundari 2010, Alzamora *et al.* 2019, Strange *et al.* 2021). In all these studies, key cost structure variables were identified as having the greatest impact on production efficiency, along with determining what proportion of sawmills operate with inefficient processes.

Stochastic frontier analysis (SFA)

The Production frontiers identify the combinations of different types of goods that a company produces when all available resources of that company are used efficiently (Ferrara 2020). SFA, which incorporates random noise by assuming a parametric composed error model, distinguishes between inefficiency and external disturbances. This approach offers more robust efficiency estimates compared to DEA techniques. A SFA model can be written as Equation 1.

$$y_i = f\left(x_i, \beta\right) + v_i - u_i i = 1, \ldots n, \quad (1)$$

Where $Y_i \in \mathbb{R}_+$ is the single output of unit $i, x_i \in \mathbb{R}_+$ is the vector of inputs, $f\left(\bullet\right)$ defines a production (frontier) relationship between the single output y and inputs x depending on the corresponding parameter vector β, v_i is a symmetric two-sided error representing random effect (noise), and $u_i > 0$ is the one-sided error term, which represents technical inefficiency; $f\left(x_i, \beta\right) + v_i$ is the stochastic frontier. It is assumed that v_i and u_i are identically independently distributed as v N (0, σ_v^2) and u N⁺ (0, σ_v^2). In SFA, the production function is modeled as a deterministic frontier function plus a random error term. Helvoigt and Adams (2009) indicate that Technical Efficiency is a measure of a production unit's operations relative to the industry's production (technical) frontier. A unit that operates on the industry's production frontier is said to be technically efficient. The deterministic frontier function is typically assumed to be a parametric function, such as a Cobb-Douglas function (Giannakas *et al*. 2003).

Generalized additive model (GAM-SFA)

The Generalized Additive Model Stochastic Frontier Analysis (GAM-SFA) presents a semiparametric technique for conducting stochastic frontier analysis (SFA). It combines the versatility inherent in Generalized Additive Models (GAMs) with the efficiency characterizing SFA (Ferrara 2020). The GAM-SFA approach encompasses multiple advantages in comparison to conventional SFA methods (Ferrara and Vidoli 2017). Firstly, it offers heightened flexibility by accommodating non-linear forms for the frontier function. Secondly, it exhibits enhanced resilience against the potential misconfiguration of the parametric structure of the frontier function. Thirdly, it enables the estimation of efficiency for individual observations, a feature absents in traditional SFA. The formulation of a GAM-SFA model is expressed as follows Equation 2.

$$y_i = \psi\left(x_i\right) + v_i - u_i i = 1, \ldots n, \quad (2)$$

Where the unknown function $\psi(\bullet)$ is modeled via GAMs to relax the linear assumption between inputs and outputs but ensuring the additivity of the input factors Ferrara (2020). Hasties and Tibshirani (1986) stated that the functions of Generalized Additive Models can be formulated as Equation 3.

$$\mu = E\left(Y|X = x\right) = \alpha + \sum_{i=1}^{p} s_j\left(X_j\right) \quad (3)$$

Where the $s(\bullet)$'s are smooth standardized so that $E\left(s_j\left(X_j\right)\right) = 0$, meaning that each smooth function is centred around zero to ensure that its contribution does not introduce bias. This standardization prevents over- or underestimation of the intercept term and preserves model interpretability, facilitating the evaluation of the relative importance of explanatory variables on a common scale.

SFA industry applications

Stochastic Frontier Analysis (SFA) finds valuable applications in the sawmill industry for assessing production efficiency and performance. Recent studies delve into SFA's foundations, advances, and estimation techniques, encompassing productivity and efficiency analyses in various industries (Kumbhakar *et al*. 2020).

The approach has demonstrated relevance in economics, particularly for evaluating firms' production efficiency (Nguyen 2020). As the sawmill industry strives for operational excellence, SFA is a potent tool for enhancing efficiency and driving informed decision-making.

Several studies in the literature report experiences in applying different types of frontiers analyses to the productivity of companies linked to the agricultural sector (Moreira *et al*. 2006, Rodríguez *et al*. 2017, Bibi *et al*. 2021), and specifically to the forest and wood industry (Niquidet and Nelson 2010, Ogundari 2010, Alzamora *et al*. 2019, Strange *et al*. 2021).

Presently, comprehensive investigations into the application of stochastic frontier models for evaluating the efficiency of Chile's sawmill sector are notably absent. The objective of this study is to examine the historical and spatial-temporal dynamics of efficiency within the sawmilling sector and efficiency, employing stochastic frontier models as a methodological framework.

Methodology

In this section, we outline the general methodology employed in this study. The databases utilized herein are those maintained by INFOR, and the overall procedure consisted of fitting two stochastic frontier models (SFA and GAM SFA). These methods were chosen because they offer more robust estimates, allowing for the distinction between technical inefficiency and random noise. Specifically, the comparison between a more rigid model like SFA and a more flexible one such as GAM-SFA provides a comprehensive understanding of efficiency impacts. The analyzed period spans from 2014 to 2022, as these years provide the most comprehensive and complete data. This approach was undertaken to establish two distinct criteria for drawing conclusions regarding the obtained results. We assessed efficiency variations across both spatial and temporal dimensions, while also statistical analysis to determine whether any patterns were associated with the volume of wood produced by the sawmills.

Sawmill system and forest prices

Annually, the Forest Institute conducts a survey of the primary forestry industry across the entire Chilean territory where the forestry sector operates, collecting data from around a thousand companies. The survey records variables such as production, consumption, machinery, and employment, among others. Part of the survey includes a cost structure divided into five items, which are: raw materials, labor, energy and/or fuel, machinery maintenance and renewal, and others.

As for forest prices, these are obtained through a quarterly survey. Prices of forest products are acquired from companies, which are selected for their product diversity and their willingness to make this data public. These prices are stored in INFOR's forest statistics platform system, where they are subsequently processed.

Variables and modeling

A Standard Linear SFA model and a GAM-SFA model (without monotonicity constraints) were used to estimate the efficiency of sawmill wood production through the cost variables and sawmill production (Table 1). The output variable of the model was the production of sawmills, while the remaining variables served as inputs to the model.

Table 1: Model variables.

Variable	Description	Abbreviation
Production	Sawn wood produced by sawmill (m^3)	P
Raw material	Estimated annual amount of log supply cost (USD)	Rm
Labor	Estimated annual amount of labor cost (USD)	L
Energy	Estimated annual amount of Energy (Electricity and/or gas) cost (USD)	E
Machinery	Annual cost of acquisition and repair of machinery (USD)	M
Supplementary	Other cost (USD)	O

The INFOR data price was converted from Chilean pesos (CLP) to United States Dollar (USD) using the official exchange rate provided by the Chilean Central Bank (Banco Central 2011). To estimate the cost of raw materials, we utilized the unit cost of logs (per cubic meter) in conjunction with the total volume of wood purchased by the sawmill (Equation 4). This initial cost formed the basis for extrapolating the remaining expenses associated with the entire production process (Equations 5). This extrapolation was facilitated by applying the percentage values provided for the sawmill in the Cost Structure section of the annual INFOR survey. The equations used are:

$$Rm = logCost * Volumepurchased \quad (4)$$

$$L = \frac{P_{Rm} Rm}{P_L}, E = \frac{P_{Rm} Rm}{P_E}, M = \frac{P_{Rm} Rm}{P_M}, O = \frac{P_{Rm} Rm}{P_O} \quad (5)$$

Where P_{Rm} is the percentage of cost use in Raw material, P_L is the percentage of cost use in Labor, P_E is the percentage of cost use in Energy, P_M is the percentage of cost use cost of acquisition and repair of machinery and P_O is the percentage of cost use in Supplementary costs.

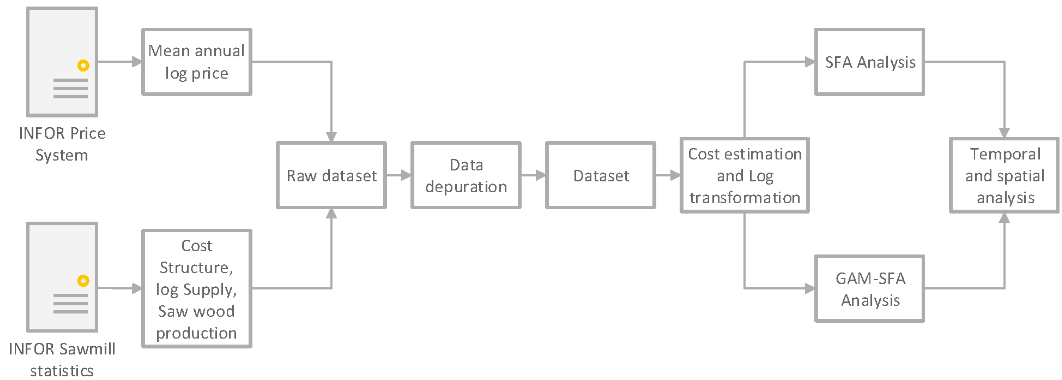

Figure 1: Methodology diagram.

The input variables underwent a logarithmic transformation $\left(log\left(x+1\right)\right)$. To fit the models, the methodology used by Ferrara (2020) was followed. The models were implemented using the "Frontier" (Coelli and Henningsen 2020) and "semsfa" Ferrara and Vidoli (2018) libraries within the R software (R Core Team 2022). The results of the models were used to conduct a temporal and spatial analysis of efficiency, as well as to observe how it behaves in relation to wood production. The methodology of this study is summarized in Figure 1.

To assess whether there exists a relationship between efficiency and the volume of wood produced by the sawmills, the Spearman correlation index (Wissler 1905) was calculated between these two variables. Furthermore, non-linear relationships among the variables were examined by applying polynomial smoothing regression methods using the ggplot library in R (Wickham 2016).

RESULTS AND DISCUSSION

This section presents the fundamental results and discoveries of this research, whose objective was to examine the historical and spatio-temporal dynamics of efficiency within the sawmill sector and efficiency in Chile. Employing meticulous analysis of data obtained from INFOR and taking advantage of the robust analytical framework of the stochastic frontier method, we have discovered compelling trends in efficiency behavior within the Chilean sawmill industry.

Dataset

During the period analyzed, a total of 12815 annual production records were extracted from various sawmills using the relevant database. For the analysis, records with complete cost structure reports and a "raw material" allocation percentage between 30 % and 80 % were selected. This range was determined following a detailed data exploration, as values outside this interval were deemed less representative.

Subsequently, this dataset was integrated with the INFOR pricing system, resulting in a final set of 159 records that included both cost structure information and details of payments for logs. The distribution of data by year and region is presented in Table 2. The significant reduction in data volume is attributed to the fact that not all units report the prices paid for logs, as participation in the survey process is voluntary.

Table 2: Number of sawmill data per year and region.

Year	Region							Total
	O'Higgins	Ñuble	Maule	Biobío	La Araucanía	Los Lagos	Los Ríos	
2014	2	-	3	5	6	-	-	16
2015	3	-	7	7	5	-	3	25
2016	4	-	5	5	6	-	1	21
2017	-	-	4	1	7	2	-	14
2018	1	-	7	6	5	-	-	19
2019	-	3	6	4	4	2	-	19
2020	-	2	6	2	-	1	-	11
2021	1	1	3	5	3	-	-	13
2022	3	4	6	4	2	2	-	21
Total	14	10	47	39	38	7	4	159

Standard SFA

The efficiency distributions produced by the SFA and GAM-SFA methods (Figure 2 and Figure 3) were generated using all available data, thus displaying calculated values for the same sawmills but across different time periods.

The input variables, raw material (*Rm*), and supplementary cost (*O*), exhibited statistical significance within the standard SFA model. In contrast, labor costs (*L*), energy (*E*), and machinery (*M*) did not demonstrate statistical significance (Table 3).

Table 3: Estimates for standard SFA.

Intercept	Estimate	Std. error	p-value
Intercept	-4,1411371	0,0805991	< 2,2e-16 ***
Rm	0,9643164	0,0126076	< 2,2e-16 ***
L	0,0104181	0,0079124	0,18794
E	0,0042103	0,0100927	0,67656
M	0,0021434	0,0030087	0,46559
O	0,0036034	0,0017605	0,04068 *

Statistical significance of the model variables with *** highly significant results ($p < 0.001$) and * significant differences ($p < 0.05$).

The estimated SFA average efficiency was 87,8 % for all the records analyzed. In all the cases, sawmill efficiency surpasses 65 %. However, the 25th percentile of the distribution is at 84,7 %, whereas the 90th quantile is at 94,7 %, indicating that majority of sawmills exhibited efficiency levels ranging between these values (Figure 2).

GAM-SFA

In the GAM-SFA model, the input factors, encompassing raw material (*Rm*), labor (*L*), and supplementary costs (*O*), demonstrated statistical significance within the standard SFA framework. However, contrary to this, the costs of energy (*E*) and machinery (*M*) did not exhibit statistical significance (Table 4). When compared to the conventional SFA, the flexibility inherent in the GAM-SFA model allows labor to attain greater significance. This is a result of the fact that GAM-SFA seeks non-strictly linear relationships between the variables, enabling a more comprehensive exploration of how these factors interact.

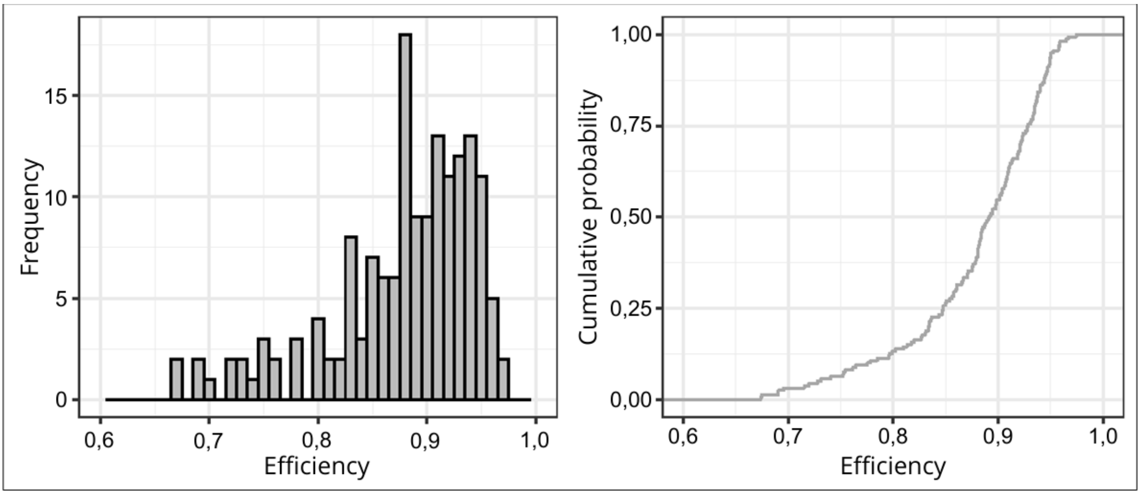

Figure 2: Efficiency distribution SFA.

Table 4: Estimates for standard GAM-SFA.

Intercept	Estimate	Std. error	p-value
Intercept	-4,374240	0,076876	< 2,2e-16 ***
Rm	0,925842	0,012435	< 2,2e-16 ***
L	0,071521	0,008983	5,8e-13 ***
E	-0,002767	0,009108	0,7618
M	-0,004094	0,002755	0,1396
O	0,004043	0,001657	0,0159 *

Statistical significance of the model variables with *** highly significant results ($p < 0.001$) and * significant differences ($p < 0.05$).

In contrast, the estimated efficiency remains similar to that of SFA, with an average of 89,9 % using all the data. The 25th percentile of the distribution is at 87,2 %, while the 90th quantile is at 94,8 %, indicating the range within which efficiencies are concentrated when utilizing the GAM-SFA method. There were very few instances with efficiencies below 80 % (Figure 3), with a distribution skewed towards the right, similar to the pattern observed with the standard SFA. However, this distribution appears more condensed, exhibiting fewer data points in the lower region of the curve.

In general, the results provided by SFA and GAM-SFA do not vary significantly, with similar means and distributions. An empirical example conducted by (Ferrara 2020) on crop data in some European regions exhibits similar behaviors to those observed in this study, in terms of the resemblances between the two explored methodologies.

The efficiency values findings align with the research conducted by Helvoigt and Adams (2009), who reported technical efficiency levels ranging from 89,6 % to 99,7 % within the USA Pacific Northwest sawmill industry. In another study on sawmill efficiency in Nigeria (Ogundari 2010), it was concluded that this industry exhibits an average efficiency of 76 %, which is significantly lower than the average calculated in this study, whether using the SFA or GAM-SFA methodology.

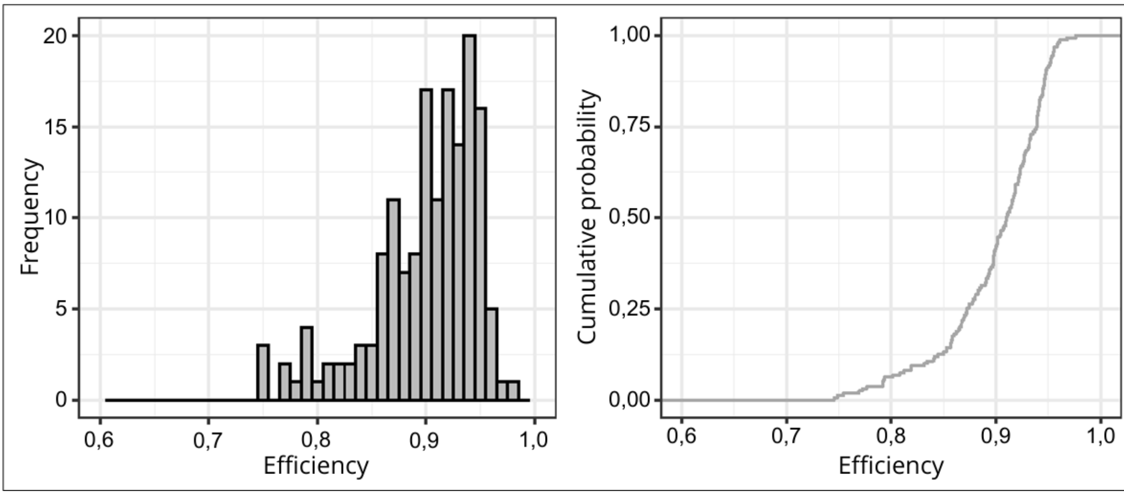

Figure 3: Efficiency distribution GAM-SFA.

Temporal and regional analysis

The estimated average efficiency for the sawmill industry exhibited dynamic behavior during the analyzed period (2014-2022) (Figure 4). Between 2015 and 2020, it maintained a certain stability, as reflected in both the SFA and GAM-SFA estimations. However, in the year 2021, there was a pronounced decline that further worsened in 2022. This abrupt change in the trend can be attributed to the impact of the COVID- 19 pandemic, as the value of logs increased significantly during this period (Pardo and Bañados 2022, Mejías 2022). Considering the context provided, it is imperative to persist in monitoring the performance of the Chilean sawmill sector, transcending the repercussions of the pandemic. This ongoing surveillance aims to ascertain whether the sector has successfully reinstated the previously documented benchmarks.

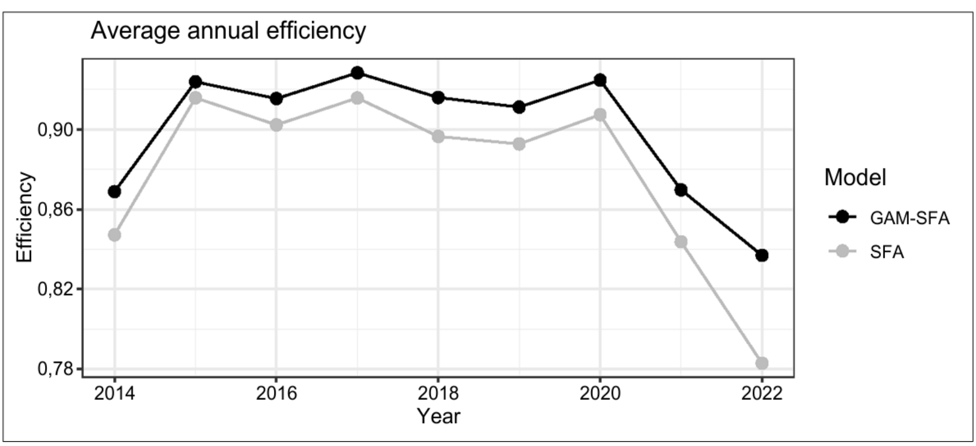

Figure 4: Average annual efficiency SFA and GAM-SFA.

Spatial analysis was conducted using all available data, resulting in averaged values calculated for the same sawmill but across different time periods. It is possible to appreciate the existence of a latitudinal pattern in sawmill efficiency, increasing from North to South (Figure 5). This phenomenon could be related to many factors related to the nature of the territories. For instance, the O'Higgins Region is not characterized by the presence of high-grade radiata pine plantations, leading to a substantial increase in the cost of quality sawlogs compared to other regions within the country. It is worth noting that in order to draw more precise conclusions about this matter, it is necessary to enhance the databases of INFOR, particularly regarding the cost structure. This enhancement will contribute to obtaining a more representative regional sample. Nevertheless, it is evident that there are clear trends that distinguish each of the regions, as seen in the case of the USA Pacific Northwest, where geographic location is a significant differentiating factor in sawmill efficiency (Helvoigt and Adams 2009).

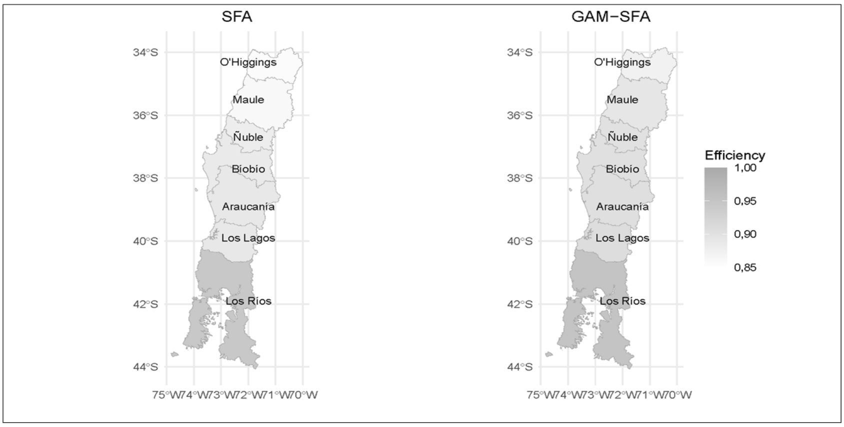

Figure 5: Average regional efficiency SFA and GAM-SFA.

Production and efficiency

Upon analysing the relationship between sawn wood production and sawmill efficiency, no clear pattern is found between these two variables (Figure 6). The Spearman correlation between these variables is very low, and even when applying a smoothing regression, no clear pattern is observed.

With this background, it is possible to say that even sawmills with low production are capable of being efficient in their process. This allows for the establishment of specific state incentives for small and medium-sized enterprises (SMEs) within this sector, aimed at enhancing their conditions to achieve higher efficiencies. Empirical evidence suggests that these SMEs have the potential to deliver superior outcomes. The promotion of improved results should be focused on the cost factors that exert the greatest influence on efficiency, including raw materials, labor, and supplementary costs. Additionally, particular attention should be directed towards the central-southern regions of the country, which exhibit lower average efficiency levels.

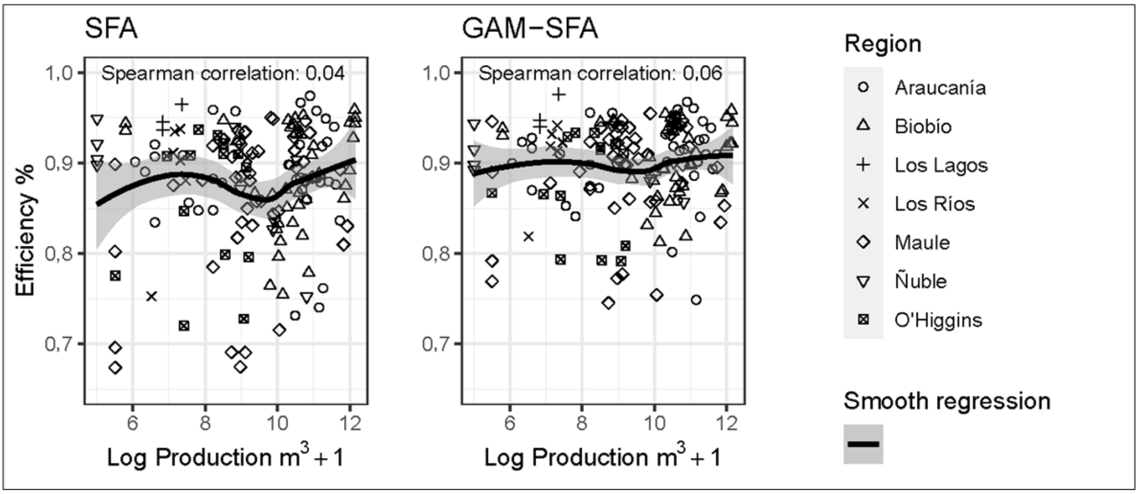

Figure 6: Relation between efficiency, logarithm of production, and regions.

CONCLUSIONS

Using the dataset gathered by INFOR, it was possible to conduct a study on stochastic frontiers by fitting two different types of models. The primary challenge in applying this methodology was the absence of a clear cost structure from sawmills, which is critical for conducting this research. Despite this obstacle, after data refinement, a consistent dataset was obtained to facilitate the methodology of this study.

Both SFA and GAM SFA methodologies yielded consistent results, revealing similar average efficiencies and distributions, indicating that sawmill efficiency ranged between 80 % and 90 %. These values are akin to those reported for the Pacific Northwest sawmill industry and exceed those for the Nigerian industry. The most relevant cost variables in the models were raw material, labor, and supplementary costs.

Temporal variations in sawmill efficiency in Chile were explored, with a noteworthy observation being a decline in this variable. After a period of relative stability (2015-2020), efficiency dropped from 0,91 in 2020 to 0,78 in 2022, according to the standard SFA results. This decline can be largely be attributed to the COVID-19 pandemic and its multiple impacts, making it crucial for future research to continue monitoring this variable.

A latitudinal trend in sawmill efficiency was identified, with regions further south in Chile demonstrating better efficiency in producing radiata pine sawn wood. This variation is likely due to the characteristics of these territories, but further data collection is necessary to draw more convincing conclusions in this regard.

No dependency was found between the volume of wood produced by sawmills and their efficiency. Consequently, it can be concluded that other factors contribute to the performance gaps. These factor must be addressed to help small-scale producers with productivity problems achieve higher levels of efficiency.

Authoship contributions

W. M. C.: Conceptualization, methodology, formal analysis, investigation, visualization, writing – original draft. P. P. H.: Writing – original draft, writing – review & editing. J. G. C.: Writing - review & editing. I. G.: Writing - review & editing. D. S. O.: Writing - review & editing.

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