Benchmarking the Performance of Logging Crews Using Stochastic Frontier Analysis

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ABSTRACT – Timber harvesting businesses do not have a standard method to quantify performance or determine the capacity of an individual logging crew. Both productivity and efficiency are often used to measure performance. Productivity is the ratio of output to input. Efficiency is a comparison or ratio between an observed performance level and a benchmark, defined as the optimal performance for a given level of input. This study used a benchmarking technique to estimate production capacity for individual logging crews as a function of labor and capital inputs. We used 3,132 weekly production reports during 2000 and 2001 from 63 logging crews. These weekly data serve as a quantitative narrative of the workweek, explaining the number and types of loads hauled, the amount of labor employed, the number of moves, and the extent of use of contract trucking. We used stochastic frontier analysis (SFA) to estimate technical efficiency. A production frontier was estimated based on actual production and measures of labor and capital inputs. Explanatory environmental variables were tested for significance and influence on production.

INTRODUCTION

Performance of a business or industry is often difficult to evaluate because the definition of performance varies between firms and industries. The business of timber harvesting, or logging, suffers from the lack of a standard method to quantify performance. In many cases, productivity and efficiency are applied as measures of performance. Productivity has been defined as the ratio of outputs to inputs (Coelli et al. 1998). Efficiency is a comparison or ratio between an observed level of output and a benchmark that is considered the optimal output level for a given level of input.

The challenge of applying these measures to any industry exists in determining what to include as input and output and how to find, measure, or estimate the benchmark. The benchmark or optimal level of production is the productive capacity or the maximum level of output attainable by a crew with a given equipment array or fixed capital input (LeBel 1993). The benchmark can be estimated in a number of ways. Each machine has a theoretical rating, based on engineering measurements, which gives the maximum output that a machine could produce in a given amount of time. The sum of the machine rates would give a measure of the productivity. This logic, however, is flawed in that the sum of the parts rarely equates to the whole. Additionally, this method allows for no stochastic or random effects in the production process. More preferred methods to estimate production capacity uses actual production data. Stochastic frontier analysis (SFA) is one widely accepted method of estimating capacity and efficiency that is based on actual production data. It also accounts for random effects in production as well as possible measurement error.

Stochastic frontier analysis estimates “best practice” frontiers, with the efficiency of specific observations measured relative to that frontier (Coelli et al. 1998). A functional form for the production frontier is specified, similar in many ways to a production function. A production function assigns the expected or average output for a given set of inputs, whereas the production frontier defines the maximum output for the same set of inputs (Figure 1). Because this method is stochastic, observations may be off the frontier due to inefficiency and/or random effects. The frontier function is hypothesized to contain a separable, two-part error term where one part accounts for inefficiency and the other accounts for random effects. The generic translog specification of a production frontier:

\[ Y_j = X_j^\ast B + (V_j - U_j) \]

where:

- \( Y \) = the natural logarithm of output of a firm;
- \( X \) = the natural logarithm of a vector of inputs to production;
- \( B \) = a vector of unknown parameters to be estimated;
- \( V \) = the error term that accounts for random effects;
- \( U \) = the non-negative error term that accounts for technical inefficiency.
By slightly modifying the original stochastic frontier function, we can produce one-stage estimations of the frontier and observation-specific efficiencies, which include the effect of environmental variables. The modification expresses the inefficiency effects, \( U \), as an explicit function of the selected environmental variables. The distributional assumptions on \( V \) are the same as the previous model, but the assumptions on \( U \) are the key difference. \( U \) is still assumed to be independent, identical, truncated at 0, and normally distributed, but unlike before the distribution of \( U \) is assumed to have a mean, \( M, [N(M, \delta_{U}^2)] \). \( M \) is expressed as a function of the selected environmental variables:

\[
M_j = Z_j \alpha G
\]

where:
\( Z = \) a vector of environmental variables;
\( G = \) a vector of unknown parameters to be estimated.

**PRODUCTION INPUTS AND OUTPUTS**

The inputs and outputs of the stochastic frontier models mirror the inputs and outputs of the production process. In our study, the number of loads of wood delivered to market each week represented production output. The total number of man-hours worked by the crew during the workweek measured the labor input. Some measure of weekly expense was also required as capital input. We used all weekly expenses, except labor and trucking, as our measure of capital input. These were based on readily available, published equipment prices and operating costs rather than utilizing proprietary, crew-specific cost data that might not be readily available to future analysts.

Using equipment cost data from Brinker (2000), we generalized the categories of equipment. We combined specific types of woods equipment into ten general equipment categories; skidders, fellers, loaders, delimiters, chippers, tracked fellers, tracked skidders, tracked loaders, harvesters, and forwarders. This measure considered only woods equipment. Trucking was not included. Using Brinker (2000), we calculated average fixed cost per year and average operating cost per scheduled machine hour.

In the logger profile data, crews reported their annual scheduled machine hours. When that information was not available for a crew, we assumed 2000 hours per year. Dividing the average fixed cost per year of each of the categories by the number of scheduled machine hours per year gave an estimate of fixed cost per scheduled machine hour for each category. This calculation expressed the fixed cost in the same units as the variable cost per scheduled machine hour. By summing the fixed and variable costs, we determined the total cost per scheduled machine hour per machine category.

Also from profile data, we knew the type and number of machines that each crew used. The number of machines in each category was multiplied by the average total cost per
scheduled machine hour per category. To account for the cost of holding and maintaining spare equipment, their cost was calculated as if it were an active piece of machinery, multiplied by 20%. All costs were summed to obtain the total equipment cost per scheduled machine hour. We multiplied the total equipment cost per scheduled machine hour by the scheduled machine hours per week to attain the capital measure or total cost per week.

RESULTS

During the course of the study, we collected 3,132 logger-weeks of data from 63 loggers, all of whom had submitted profile information and at least 13 weekly activity reports. It was assumed, given the nature of the logging industry, that the technology used to sever, process, and transport wood did not change significantly during the 18 months of this study. Based on this assumption, the data panel was pooled into a single cross section of 3,132 weekly observations to simplify the analysis and present more robust findings.

Using specialized software (Coelli 1996) to estimate stochastic frontiers, we fit the data to a production frontier. The analysis resulted in the following logging production frontier model:

\[ Y = -31.4257 + 6.8849*K + 1.1523*L - 0.3848*K^2 - 0.0444*L^2 \]

where

- \( Y \) is the natural logarithm of loads per week,
- \( K \) is the natural logarithm of the capital measure, \$/week
- \( L \) is the natural logarithm of man-hours per week.

This model yields weekly production capacity that is unadjusted for environmental variables. From this estimated capacity, efficiency scores were generated for each observation. The mean efficiency value is 62.9%, with a minimum of 4.6% and a maximum of 96.4% (Figure 2). The signs (positive or negative) and magnitudes of the coefficients of this frontier relate important information. Because the coefficients for \( K \) and \( L \) are positive, we know that additional inputs of \( K \) and \( L \) will increase output, however, because the coefficients for the squared terms are negative, we know that the production process displays diminishing returns.

To address the sensitivity of the output frontier to changes in input values, we used the function to predict the production capacity using the mean values for capital and labor. We then increased and decreased each of input by 10% to examine the resulting change in output (Figure 3).

CONSISTENT PRODUCTION

Because the data were collected and expressed in weekly units, we were concerned that the frontier could be biased by “heroic” weekly efforts that would not be generally reproducible on a consistent basis by any crew. This could potentially exaggerate the productive capacity of the harvesting force and the inefficiency associated with it. To address this issue, we collapsed the data from weekly figures into both monthly and quarterly measures and performed similar stochastic frontier analysis on these collapsed datasets. To collapse the data, we simply calculated average weekly values of loads hauled and man-hours for each crew by month and quarter. By averaging the data we sought to dilute the effect of any “heroic” weeks, without completely removing them. Logger-months in which two or fewer weeks were reported were removed from the data set. We expected values for the weekly frontier to be higher than those for a monthly frontier and
likewise those for a monthly frontier to be higher than those for a quarterly frontier.

A production frontier was fit to the monthly data \((n=734)\) as described above and resulted in the following equation:

\[
Y = -22.8495 + 4.1565K + 2.3657L - 0.2287K^2 - 0.1558L^2
\]

where

\(Y\) is the natural logarithm of average loads per week,
\(K\) is the natural logarithm of the capital measure,
\(L\) is the natural logarithm of average man-hours per week.

This function yielded production capacity, expressed as an average weekly value, as determined on a monthly basis that is unadjusted for environmental variables. Based on this frontier, 734 efficiency scores, one for each observation, were produced. The mean efficiency value is 65.9%, with a minimum of 14.6% and a maximum of 92.9% (Figure 4).

Quarterly data were obtained using the same process as with monthly data. Logger-quarters with fewer than seven weeks reported were dropped from the data set. We fit a production frontier on the quarterly data \((n=259)\), forming the function:

\[
Y = -25.5648 + 5.0329K + 2.0129L - 0.02802K^2 - 0.1241L^2
\]

where

\(Y\) is the natural logarithm of average loads per week,
\(K\) is the natural logarithm of the capital measure, \$/week
\(L\) is the natural logarithm of average man-hours per week.

This function yields production capacity expressed as average weekly production, but determined on a quarterly basis and is unadjusted for environmental variables. Based on this frontier, 259 efficiency scores, one for each observation, were produced. The mean efficiency value is 63.8%, with a minimum of 15.5% and a maximum of 92.9% (Figure 5).

Using the same production data and adding to it the corresponding environmental variables, we used FRONTIER (Coelli 1996) to produce a production frontier, including coefficients that describe the effect of the 14 environmental variables (Table 1).

### Table 1. The coefficients of the production frontier, including environmental variables.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coefficient</th>
<th>T-ratio</th>
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<tbody>
<tr>
<td>b₀</td>
<td>3.2426</td>
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<tr>
<td>b₁</td>
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<td>b₂</td>
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<tr>
<td>z₁₀</td>
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<td>8.70</td>
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Because the environmental variables are analyzed as part of
the separable, two-part error term, the coefficients describe
the effect that the variable has upon inefficiency. Thus, a
negative coefficient implies that the variable tends to reduce
inefficiency, thereby increasing efficiency. Of the 14
environmental variables, 12 appear are significant at the 99
percent confidence level (t ratio = 2.576). Only ‘stumpage
via dealer’ and ‘age of crew’ are not statistically significant.

As we expected, preferred supplier status reduced the
inefficiency of the individual crew. This could be due to a
more stable level of productivity, caused by the mill
allowing the logging contractor to more accurately tailor his
operation to that level. Stumpage via company appears to
reduce inefficiency as well. This is also likely due to a more
stable production level. Partial cut crews tend to be more
inefficient. This should be no surprise given the size of the
trees being harvested and the care required to remove the
harvestable trees while leaving standing stock intact.
Contractors that are primarily hardwood producers appear
more inefficient than those that are not. This is probably
due to the challenging terrain often inherent in hardwood
logging operations. Understandably, many loggers prefer
that the liability and expense of trucking be borne by a third
party, but in terms of production, surrendering control of
this aspect of the operation tends to reduce efficiency.
Using age of business as a proxy for experience, it seems
that experience reduces inefficiency. Selling through a
dealer tends to decrease inefficiency. This could be due, in
part, to the dealer having a variety of outlets to which he
may sell wood, even when the logger is unable to do so.
Moves, as expected, seem to increase inefficiency.
Operating in the piedmont, versus the coastal plain tends to
increase inefficiency, and operating in the mountains tends
to increase inefficiency even more. As average haul
distance increases, inefficiency increases slightly. High
tract rating also has an effect on inefficiency. The better the
tract rating (closer to 1), the less inefficient the crew
appears. Conversely, the worse the tract rating (closer to 3),
the more inefficient the crew appears.

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