UTILIZATION OF LOGGING CAPACITY IN THE SOUTHERN UNITED STATES AND MAINE

by

JAMES MILTON CHUMBLER

(Under the direction of W. Dale Greene)

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 as measures of performance. Productivity is the ratio of output to input. Efficiency is a comparison or ratio between an observed level of output and a benchmark, defined as the optimal level of output (capacity) for a given a level of input. This study attempts to define input, output, and a benchmarking technique to estimate utilization of production capacity for individual logging crews. Approximately 60 logging crews provided weekly production data during 2000 and 2001. The weekly data serves 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. To estimate technical efficiency, stochastic frontier analysis (SFA) was applied. A production frontier was estimated based on production, labor, and capital expense estimate. The capital expense estimate uses each crew's scheduled machine-hours and equipment mix to predict a cost per scheduled machine-hour. Explanatory environmental variables were tested for significance and influence on production. SFA shows great promise as a means to benchmark logging crew production capacity.

INDEX WORDS: Logging Efficiency, Logging Capacity, Stochastic Frontier Analysis

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TABLE OF CONTENTS

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Timber harvesting has evolved as a business. Initially, logging operations were manually intensive, required a relatively low capital investment and produced low levels of output. The harvesting contractors of today conduct businesses that utilize expensive machinery, requiring skilled labor and significant capital investment. This technological evolution has forced loggers to focus on higher production levels to earn profits. Like any other business, those firms that execute their tasks with a higher degree of performance tend to earn higher profits, remain in business, and prosper. To that end, the objectives of this study are:

- To assess a method of logging performance evaluation,
- To use that method to gauge the level of performance in the logging industry in Maine and the southern United States,
- To examine factors associated with varying levels of performance, and
- To demonstrate an application of the method for a single, hypothetical logging crew.

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 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. The benchmark is the optimal value of output for a given a level of input. Koopmans (1951) and Debreu (1951) originated the analyses of efficiency. Koopmans (1951) provided a definition of what is referred to as technical efficiency: an input-output vector is technically efficient if, and only if, increasing any output or decreasing any input is possible only by decreasing some other output or increasing some other input (Fare and Primont 1994). This definition implies that for a given set of inputs there exists some optimal set of outputs, or a benchmark. Charnes and Cooper (1985) remind us that Koopmans' definition and thus the benchmark should be regarded as a relative notion, relative to the best observed practice in a reference set or comparison group (Fare and Primont 1994)

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. For example, 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 could give a measure of a benchmark. 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. A better estimate of production capacity would be based on actual production data, or recalling Charnes and Cooper (1985) *best observed practice*.

Stochastic frontier analysis is a widely accepted method of capacity and efficiency estimation that is based on actual production data and accounts for random effects in production as well as possible measurement error (Coelli 1996). From a set of empirical production data, observed inputs and outputs, stochastic frontier analysis generates a production frontier, or benchmark. From the estimated frontier, or benchmark, an efficiency score is calculated for each production observation. Stochastic frontier analysis is an econometric approach to estimate efficiency and production capacity and therefore has a measure of variance, from which statistical tests can be performed.

Inputs to the production process such as capital and labor affect productivity and efficiency, but there are also other factors that govern the ability of firms to transform their available inputs into outputs. These factors could be the regulatory climate of the operation, the physical environment of the operation, or even the experience level of the firm. These factors are referred to as environmental variables in the literature and should be examined in conjunction with the typical measures of capital and labor. Stochastic frontier analysis provides such a method for analysts to incorporate environmental variables into the estimation of capacity and efficiency.

In this study, I will use stochastic frontier analysis (SFA) to estimate logging capacity, based on the benchmark. From the benchmark, technical efficiency will be calculated. Then, I will examine environmental variables to determine their relationship with technical efficiency.

CHAPTER 2

LITERATURE REVIEW

Logging Capacity

When examining the efficiency of logging crews, the procurement philosophies of the consuming mills must also be examined. To begin to understand the effect of the consuming mills on the logger, Laestadius (1990) compared the wood-supply systems in Sweden and the southern United States and found that the systems are fundamentally different. In Sweden, mills carry much higher inventories, which buffer the timber producers from variation in the mills' demand. Swedish logging crews tend to be very efficient due to this stability in production. In the southern United States, mills maintain low inventories, but keep a substantial amount of unused logging capacity available. This unused logging capacity is the mills' buffer against varying demand in consumption. Maintaining this idle capacity in the wood supply system drives down the relative efficiency of American logging crews when compared to the Swedish logging crews. He explained these differences by the different accounting focus in each system. The Swedes account for capacity while the Americans account for the cost of the wood.

In his work on logging costs, Loving (1991) obtained information on unused logging capacity by comparing loggers' highest sustainable weekly production recorded in the past years with their production at the time of the study. For the loggers he studied, he reported an overall logging capacity utilization of 51-59 percent. Although he did not attempt to quantify the actual costs of unused capacity, Loving suggested that the cost of excess capacity is passed from the company to the independent contractor in the short term with the wood consumer ultimately paying for the cost of excess logging capacity.

Later, using daily production data from 22 independent contractors, LeBel (1993) found that median efficiency was 70 percent for the study' sdgger-participants. The most frequent causes of lost production were adverse weather, quota, and moving between tracts. Other causes included problems associated with equipment breakdown and labor. Partly due to unusually inclement weather in the data collection period, rain had the most impact on logging production and was much more significant than quota. He cautioned, however, that what weather does not claim from the extra capacity, limiting quota will, since reduced wood orders are generally the only available mechanism for reducing logging capacity. As an alternative to supporting an overbuilt logging workforce, he suggested that mills maintain a smaller number of better equipped producers, which could facilitate procurement by better matching operations, tracts, and seasonal conditions.

Carter (1993) used stochastic frontier analysis to examine the efficiency of pulpwood producers in the southern United States for the years 1979 and 1987. His results indicate that the mean industry technical efficiency was nearly constant at 60 percent in both years, while production levels increased. This finding indicates that the industry had grown between those years and elevated the benchmark capacity.

LeBel (1996) used data envelopment analysis to examine the technical efficiency of a sample of logging contractors in the time period 1988-1994. The loggers in his sample tended to move from periods of high efficiency to periods of low efficiency with some contractors showing more stable efficiency trends than others. He found that those with the most stable technical efficiency levels had status as a preferred supplier to a market. For his sample, the most productive scale size was between 60,000 and 80,000 tons per year and this production level also produced at the lowest cost. Scale was important, accounting for about one quarter of the inefficiencies that he examined.

Shannon (1998) evaluated productivity, cost, and technical efficiency using a sample of 192 firm-years of data from 35 southern USA logging contractors. He found that demographic information was not highly correlated with these measures. Instead, he observed that firms with relatively low proportions of their costs in equipment and consumable expenses tended to have the highest median efficiency scores. The contractors with the highest median efficiency levels produced between 60,000 and 100,000 tons per year. Efficiency increased as the percentage of pine harvested increased. Those who purchased their own timber tended to be less efficient. Contractors with stable production levels were found to be most efficient.

Walter (1998) focused on the relationships between productivity and efficiency using the same dataset as LeBel (1996) that contained 23 crews between 1988 and 1994. During this time period, most contractors increased their production but these production gains often came at the expense of their technical efficiency. He found that firms that hauled their own wood had significantly higher efficiency that those using contracting. He found no obvious economy of scale with increasing operation size.

In a study designed to establish a baseline for measuring improvements in production and economic efficiency of loggers over time, Stuart and Grace (1999) investigated the following logging-associated costs: equipment, consumable supplies, labor, contract services (e.g., trucking), insurance, and administration. They concluded that cost reduction by increasing output appeared to have "lost effectiveness as a general strategy;" while reduced production resulted in increased cost per unit in 30 of 37 occurrences.

During the 1990s many forest products companies implemented preferred supplier systems in an effort to address many of the problems associated with logging production variability and to help keep their most promising contractors. In December 2000, the Forest Resources Association conducted a survey of the logging industry to gauge its financial health (FRA 2001). They found strong interest on the part of loggers and wood dealers for preferred supplier systems and long-term delivery contracts.

Stochastic Frontier Analysis

Frontiers or benchmarks have been estimated using a variety of different methods. The two principal methods are data envelopment analysis (DEA) and stochastic frontiers that involve mathematical programming and econometric methods, respectively (Coelli *et al.* 1998). Stochastic frontiers have a substantial advantage relative to DEA. Data envelopment analysis assumes all deviations from the frontier are due to inefficiency. If any noise is present, such as measurement error, this can influence the placement of the DEA frontier, and therefore the calculation of efficiency, more than would be the case with the stochastic frontier approach. Stochastic frontier analysis is likely to be more appropriate than DEA in agricultural applications, where external, and often random and uncontrollable forces, such as weather, heavily influence the data.

Stochastic frontier analysis produces a production frontier based on observed outputs and inputs. The frontier can take different functional forms. The simplest production form is the Cobb-Douglas production function. This functional form has been used in many studies and for many industries, but is not typically adequate to describe the reality of production. Christensen and Greene (1976) developed the translog production function. Since that time, the translog production function has become a very popular functional form due to its flexibility to fit empirical data, especially in agricultural applications (Debertin 1986). This function models the natural logarithm of output as a function of natural logarithms of inputs to production. A common specification of the translog production function is:

$$\ln (Y) = \ln a + B^*\ln (X_1) + C^*\ln(X_2) + G^*\ln (X_1) \ln (X_2),$$

where: Y is output,

X_1 and X_2 are inputs, and

a, B, C and G are parameters to be estimated.

When G is equal to zero, the production function becomes Cobb-Douglas in form. The squares of the inputs are also often included in the model, following Taylor series expansion of a production function (Debertin 1986). The stochastic frontier analysis in this study will use variations of these functional forms.

Ajibefun *et al.*(1996) used stochastic frontier analysis to estimate technical efficiency of farmers in Nigeria. Environmental variables, or factors other than direct inputs to production that affect technical efficiency, such as experience of the farmer and type of labor used, were also investigated using stochastic frontier analysis. The translog production frontier was utilized. They estimated the mean technical efficiency to be 82%

with a minimum of 19% and a maximum of 95%. The environmental variables provided insight into the trends of efficiency in the farmers. For example, younger farmers tended to be more efficient that older farmers. This is thought to be due to the younger farmers' willingness to adopt technology and abandon more traditional methods of cultivation.

CHAPTER 3

METHODS

Recruiting Study Participants

All logging contractors who took part in the study did so on a voluntary basis. Logging crews were recruited for participation in the study using a variety of techniques. Given the large geographic area covered by this study, participants were recruited and began data reporting in a couple of states each month or so until all parties were reporting. Recruiting began in South Carolina, Georgia, and Florida, and then expanded to Maine, Alabama, and Texas. These states were targeted first since they were represented by logger association members of WSRI and contained numerous mills owned by forest products companies belonging to WSRI. Our final recruiting efforts took place in Arkansas, Louisiana, Mississippi, Virginia, and North Carolina. The logger association in each of these states was not a WSRI member (Greene *et al.* 2002).

Recruiting logging crews to participate in the study presented a unique set of challenges. Each logging crew had to be individually recruited. The recruiting team did not have the advantage enjoyed with mills where senior managers sent the word to dozens of mills to be ready to participate in the weekly reporting phase of the study. Nor did the team have the benefits experienced by previous studies of unused logging capacity of either developing long-term relationships with a core of logging crews in a specific geographic locality, or of "encouraging contractors" to report who were directly affiliated with a specific wood-consuming entity. Indeed, the broad geographic focus of this project sacrificed the advantages associated with these approaches in favor of improved representation over a broader region. In addition, the weekly reporting of production information by loggers likely improved the reliability of the data versus that obtained by other methods.

Loggers were contacted individually in a variety of ways. First, wherever possible and whenever our schedules permitted, the team tried to solicit participation in person. The team attended dozens of meeting held by these logger associations. Some of these were annual state meetings, others monthly or quarterly district meetings within a state. The association executives were asked to use their periodic newsletters to help enroll their members. We also asked each state logger association to send a letter that we composed on their letterhead and over the signature of their president or executive director to each logger member asking them to participate. Each state logging association had contributed financially to WSRI, thus they had a stake in seeing the study off to a successful start. These techniques approached only logging crews who were members of the logger association. Since we did not wish to bias the study by only recruiting from this pool of logging crews, we did not confine our recruiting solely to this group.

In addition, whenever a mill agreed to participate in the study, we asked them for a list of wood suppliers or logging crews who delivered wood to their facility. Some mills provided the names of all those who delivered wood to them while others supplied only the names of suppliers or crews who delivered a significant portion of their wood receipts. Regardless, this method provided a list of names that included logging crews that were member and non-members of the state logging association. We then mailed a letter to every logging crew named on the list provided by each mill, explaining the study to them and asking them to take part. Those who elected to participate returned a form to us by regular mail or fax.

Data Reporting

Once a logging crew volunteered to join the study, we sent them a blank profile form that asked them to describe their system. We also sent them a blank weekly reporting form either as multiple printed copies or an electronic spreadsheet file (Appendix A). We designed the study to collect production information each week. Logging crews reported actual production and missed production with reasons assigned for missed production. Every logging crew participating in the study received an on-site visit from a member of the research team. This visit took place before or just after the crew began reporting weekly data. This was often necessary to get data reporting underway (Greene *et al*. 2002).

Estimating Capacity

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 the 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, one part accounting for inefficiency and the other accounting for random effects. In Figure 1, the data point represented at A is on the frontier, operating at capacity and is therefore deemed 100% efficient. Data point B is below the frontier, operating below capacity, at a level of efficiency less than 100%. The distance from B to the frontier is the measure of inefficiency, accounted for by the inefficiency error term. The generic translog specification of a production frontier is:

$$Y_j = X_j{*}B + (V_j - U_j) \qquad j = 1, \ldots, N$$

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, and

U = the non-negative error term that accounts for technical inefficiency.

The distributional assumptions placed on V, the random effects error term are that they are normally, identically, and independently distributed with a mean of 0 and variance of sigma squared. Additionally, they are assumed to be independent of U, the inefficiency term, which are assumed to be half-normally distributed, truncated at 0, and independently and identically distributed among themselves, N(î , ö$_U^2$)|.

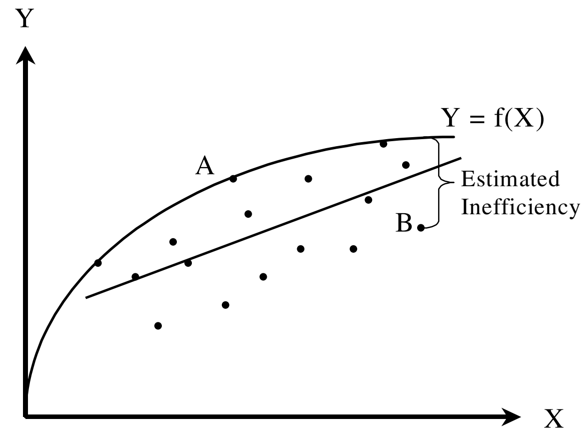

Figure 1. A generic production frontier, fit over sample data with an Ordinary Least Squares regression line fit. Relative efficiency and inefficiency is demonstrated for data point B.

By simply using the inputs of the production process, stochastic frontier analysis (SFA) reveals much information regarding the efficiency of each observation. In fact, each observation has a technical efficiency percentage associated with it after SFA is performed. The logical next step is to try to explain these efficiencies using information about the firms and operating conditions that produced the observations. This information, often referred to as environmental variables, may encompass any information external to the production process, not just the physical environment. A number of empirical studies have estimated stochastic frontiers and predicted firm-level efficiencies, and then regressed the efficiencies upon firm-specific variables. Variables such as region, firm experience, or business strategies were used to identify some of the reasons for differences in predicted efficiencies between firms within an industry (Coelli 1996). While this is a useful exercise, it is inconsistent in its assumptions regarding independence of the inefficiency error term. Also, this two-stage procedure is unlikely to produce estimates that are as efficient as those obtained using a single stage procedure (Coelli 1996).

Environmental Variable Analysis

By slightly modifying the original stochastic frontier function, one can produce one-stage estimations of the frontier and observation-specific efficiencies, which include the effect of environmental variables. This modification expresses the inefficiency effects, U, as an explicit function of the selected environmental variables. The distributional assumptions on V are the same as for 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 mean, M, $|N(M_j, \sigma_U^2)|$. M is expressed as a function of the selected environmental variables:

$$M_j = Z_j * G$$

Where:

Z = a vector of environmental variables;

G = a vector of unknown parameters to be estimated.

This method provides technical inefficiency scores, accounting for environmental difference between firms. The estimated coefficient for each environmental variable included in the analysis indicates the magnitude of effect the variable imposes on inefficiency. A positive coefficient indicates that the variable is associated with increasing inefficiency. Conversely, a negative coefficient indicates that the variable is associated with decreasing inefficiency.

Quantifying Production Inputs and Outputs

The inputs and outputs of the stochastic frontier models mirror the inputs and outputs of the production process. In this case, the number of loads of wood delivered to market each week represents production output. The total number of man-hours worked by the crew during the workweek measures the labor input. Some measure of weekly expense is also required as capital input. In this context, weekly capital inputs are all expenses, except labor and trucking. For the purposes of this analysis and to establish this method as a useful tool for future investigators, a capital estimate was developed. The estimate expresses average weekly capital inputs (expenses), 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 (2002), the categories of equipment were generalized. Specific types of woods equipment were combined resulting in ten general equipment categories: skidders, fellers, loaders, delimbers, chippers, tracked fellers, tracked skidders, tracked loaders, harvesters, and forwarders. This capital estimate considers only woods equipment. Trucking is not included. Using Brinker (2002), average fixed cost per year and average operating cost per scheduled machine hour were determined (Appendix B).

In the logger profile data, the annual scheduled machine hours per crew were reported. If that information was unavailable for any crew, 2000 hours per year was assumed. 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, I determined the total cost per scheduled machine hour per machine category.

Also from profile data, the type and number of machines that each crew used was known. 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, the cost was calculated as if it were an active piece of machinery, multiplied by 20%. These costs were summed to form the total equipment cost per scheduled machine hour. I multiplied the total equipment cost per scheduled machine hour by the scheduled machine hours per week to attain the capital estimate or total cost per week.

Environmental Variables

Since data were available regarding the operating environment and business strategies of the cooperating producers, I attempted to explain some of the inefficiency. Fourteen environmental variables were selected based on their availability and perceived importance to inefficiency. These variables were:

Prefer – was the crew is a preferred supplier to any mill? Preferred supplier status should positively influence efficiency in production, firstly, because a logger must have displayed good practices in order to earn the status and secondly, due to preferential treatment in terms of wood order stability, quality of tract, etc.

Stumpage via company – did the mill provide stumpage? This could logically be either positive or negative. In the positive light, you might expect the company to provide a stable source of stumpage, thereby freeing the logger to concentrate efforts on other aspects of the business. However, just as likely a scenario is the mill does not provide a truly stable source of stumpage, but the logger has come to rely on it and now has less control of his business.

Stumpage via dealer – did the crew acquire stumpage through a dealer? This variable simply accounts for a dealer being involved in any portion of stumpage acquisition. It could prove positive, because a dealer is another source of stumpage, or it could prove negative because a dealer is often merely another pair of hands for the wood to flow through.

Partial – was the crew a thinning or diameter-limit-cut crew? Partial cut crews should be less efficient that clear-cut crews due to the smaller size of the trees, and the extra caution that must be expended to spare the residual trees.

Hardwood – was the crew primarily a hardwood producer? Hardwood producers could be expected to be more efficient due to less market restriction on hardwood pulpwood. However, it is more likely that a hardwood crew would be less efficient due to the adverse areas where many of the hardwood species grow and the extra time and labor required to delimb and buck a hardwood tree as opposed to a pine.

Contract Trucks – did the crew primarily use their own trucks for the transport of wood? Trucking is a vital component in the production of wood, and the out-sourcing of hauling has proven efficient in many industries.

Business age – how long had the business been in operation? We used this as a proxy for experience. Efficiency should be positively impacted by more experience.

Crew age – how long had this particular crew been in operation? Again, this was another proxy for experience. The longer the crew had been in operation, the higher the efficiency should be. But this may be confounded by the fact that a new crew could be comprised of some of the better employees pulled from an older crew.

Market Access – was a dealer involved in selling any portion of the crew's wood? This could be positive in that a dealer could have more outlets through which to sell the wood, or it could be negative in that a dealer might be seen a merely another pair of hands through which wood flows.

Moves – the number of moves in a given week. Efficiency should suffer with increasing moves.

Piedmont – did this crew operate primarily in the Piedmont or similar areas? The Piedmont should slow down producers from a pace that would be expected from a similar coastal plain producer.

Mountain – did this crew operate primarily in mountainous areas? Mountainous conditions should further slow down production from the pace set by a similar Piedmont producer, when compared to a coastal plain producer.

Average miles – the weighted average of haul distance to mills. As the haul distance increased, efficiency should suffer.

Tract rating – the highest daily tract rating for the week, good (1), fair (2) or poor (3), as perceived by the logger. Efficiency should suffer as tract rating worsened (increased).

CHAPTER 4

RESULTS

Participants

A total of 83 logging crews signed up to participate in the study and completed a logging crew profile form (Figure 2). These 83 crews collectively provided 3,188 crew-weeks of production information. Twenty of these crews provided fewer than 13 weeks of weekly production reports and were not used in these analyses due to their extremely small dataset. This left 63 crews whose weekly production data formed the dataset used for most analyses. Of these 63 crews, 29 provided more than four quarters of weekly data. Thirty-two (32) crews delivered more than 2000 loads of wood during their data reporting weeks (Figure 3). Geographically, crews were well distributed across the study region with five or more crews reporting at least one quarter of data from eight states (AL, FL, GA, ME, MS, SC, TX, VA).

Logging crews were about equally split between those that were preferred suppliers (n=30) and those that were not (n=33) (Figure 4). These crews were organized in a variety of legal ways with corporate structures (C or S) being by far the most common (Figure 5).

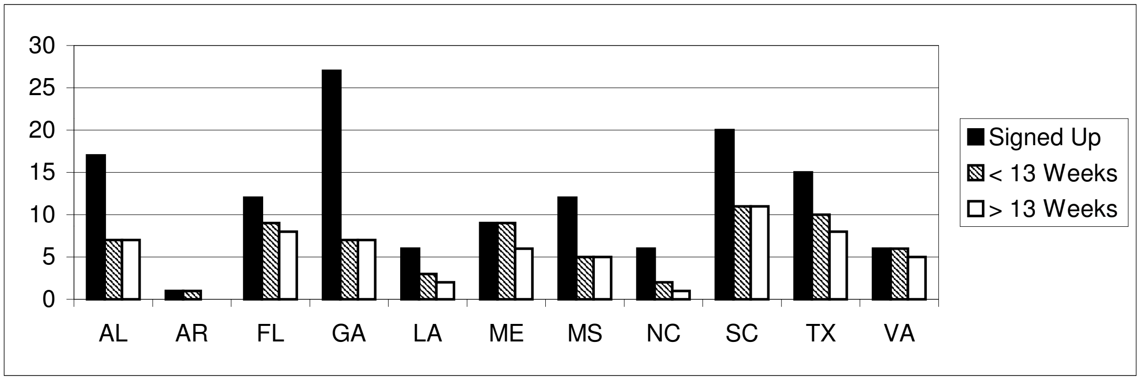

Figure 2. Number of logging crews providing profile and weekly production data.

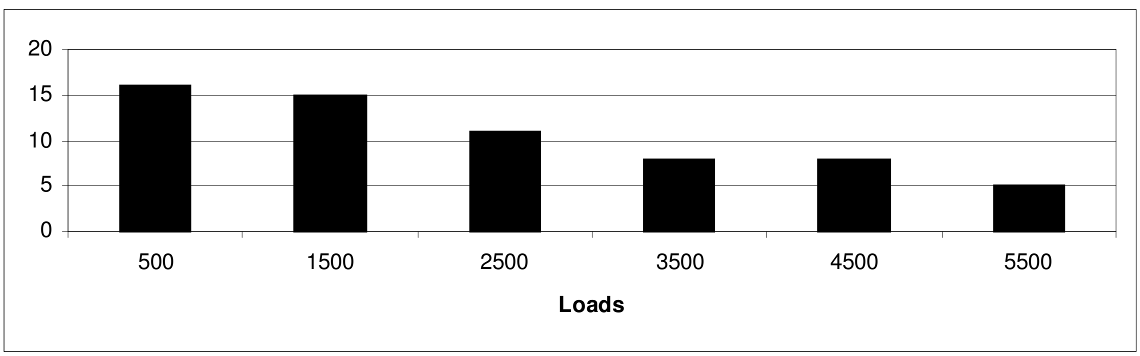

Figure 3. Number of loads delivered by logging crews that reported more than 13 weeks of data.

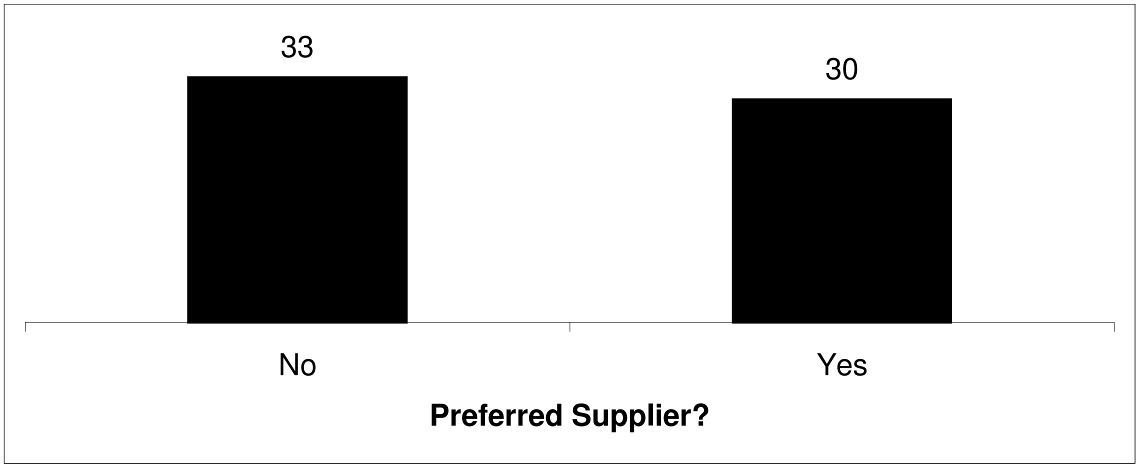

Figure 4. Status of logging crews as preferred suppliers.

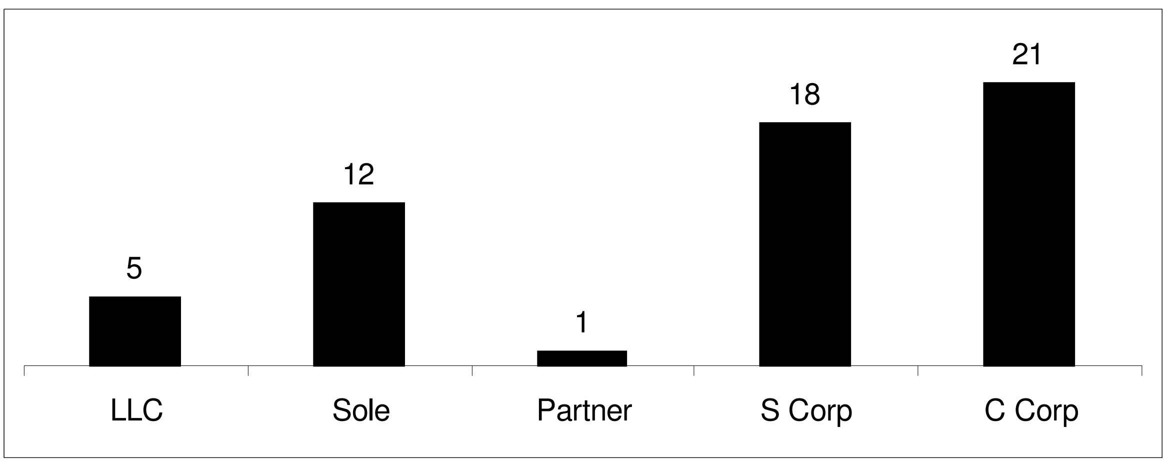

Figure 5. Number of crews by type of business organization.

Stumpage access (Figure 6) was obtained by a range of methods with the logger obtaining his own reported 24 times, the company providing it reported by 19 crews, and a dealer providing it reported by another 12. Market access (Figure 7) was overwhelmingly reported to be a direct relationship with a market company (n=38) compared to through a dealer (n=17). Eight crews did not answer the above two questions. Combining the information from both of these questions, 19 crews had some form of relationship with a wood dealer while the remaining 44 had no such relationship (Figure 8).

Most crews produced roundwood (n=47) while another eight primarily produced chips (Figure 9). Clearcutting was the primary (>50% of time) harvest method for 34 crews while thinning was the primary harvest method for 15 crews (Figure 10). Pine or softwood species were the primary focus of 45 crews compared to 12 crews that focused primarily on hardwood species (Figure 11).

Figure 6. Sources of stumpage for logging crews.

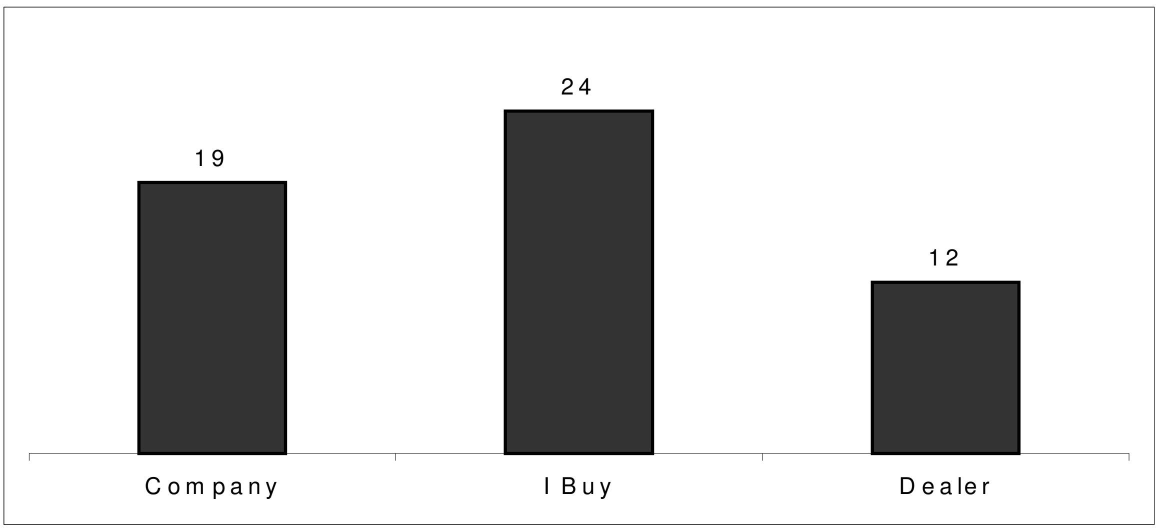

Figure 7. Access to market companies for logging crews.

Figure 8. Presence of any dealer relationships for logging crews.

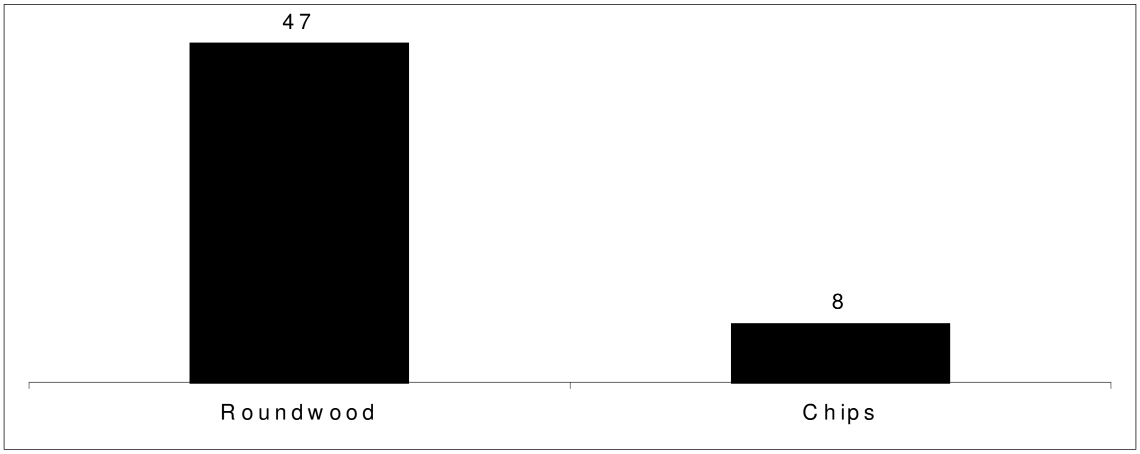

Figure 9. Primary types of products produced by logging crews.

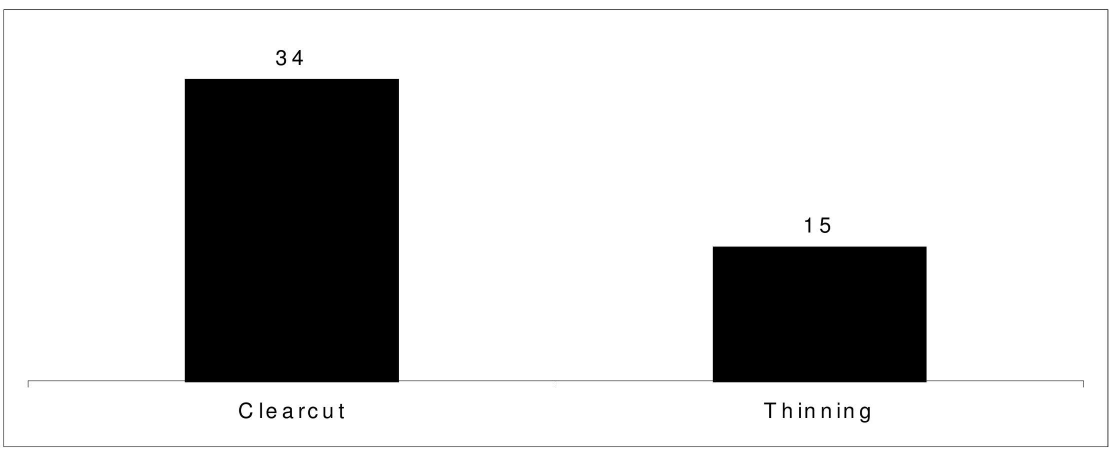

Figure 10. Primary types of harvests performed by logging crews.

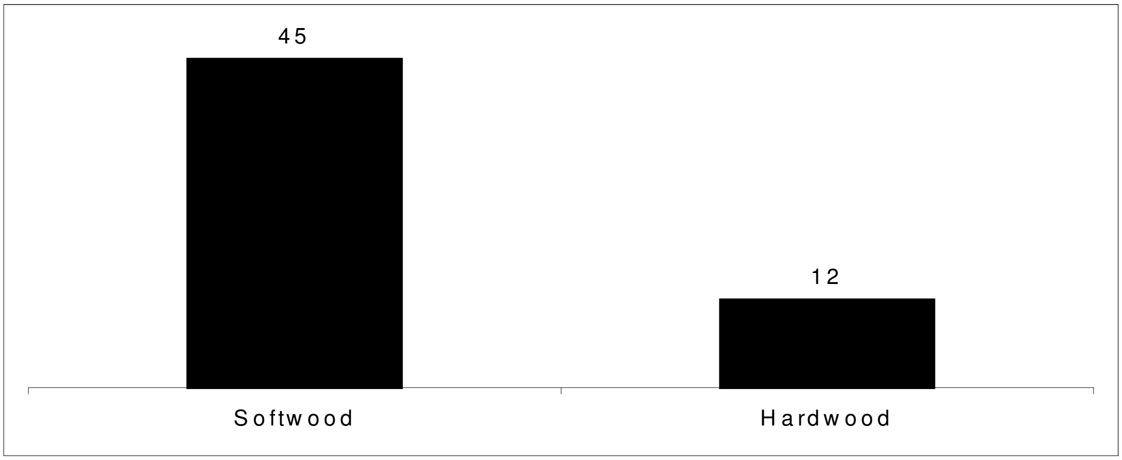

Figure 11. Primary species harvested by logging crews.

Each crew was also asked to estimate their sustainable production capacity, give their target weekly production, and state their break-even weekly production level. Most crews reported production capacities between 50 and 80 loads per week (Figure 12). Target production levels typically ranged from 30 to 80 loads weekly (Figure 13) while break-even levels were generally between 25 and 60 loads per week (Figure 14). To see how estimates of capacity and target production related to break-even levels, these were examined as a percentage of the break-even level. Crews generally stated their capacity to be 30-50% greater than their break-even level (Figure 15) with their weekly target production 10-30% greater than break-even (Figure 16). To put this in perspective, for a crew with a break-even level of 60 loads, targeting production at 20% over break-even implies a target of 72 loads or 14.4 loads per day on a five-day week. Missing one day of production drops the crew below their break-even level (72-14=58 loads). Many of these crews are thus working close to their perceived break-even levels. Crews commonly targeted a working year of 245 to 260 days (Figure 17).

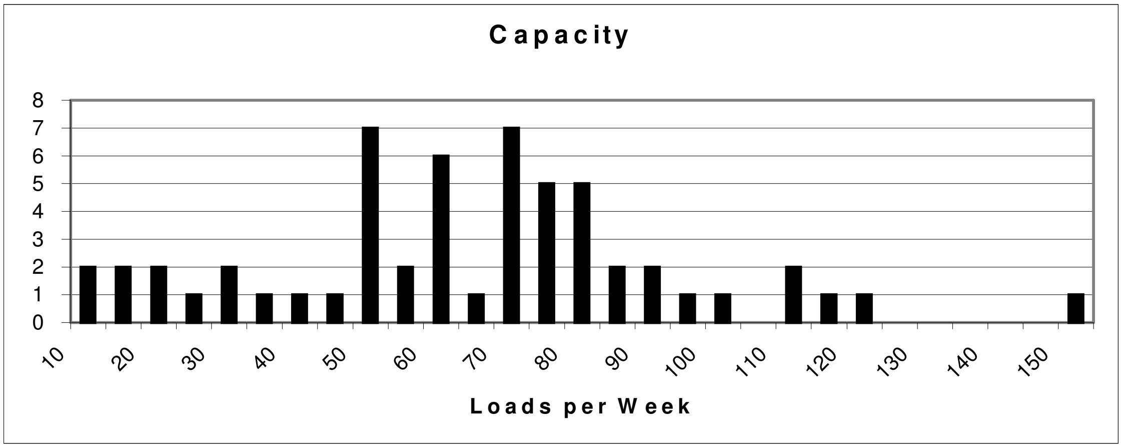

Figure 12. Capacity levels estimated by logging crews.

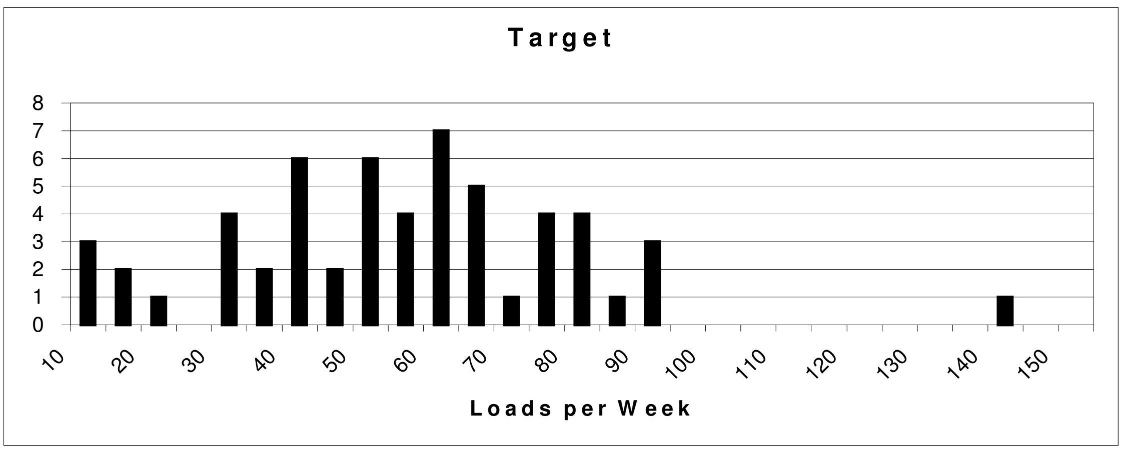

Figure 13. Target weekly production levels for logging crews.

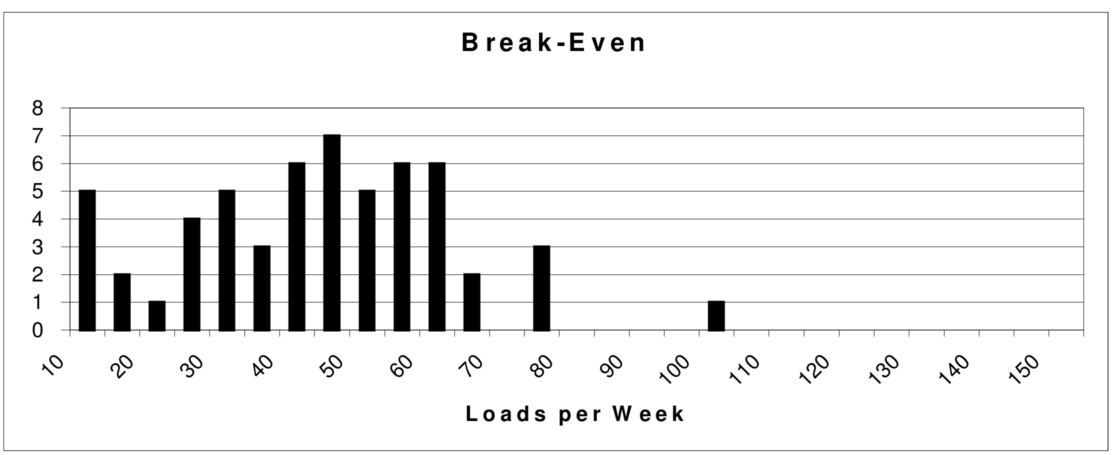

Figure 14. Estimates of break-even levels for logging crews.

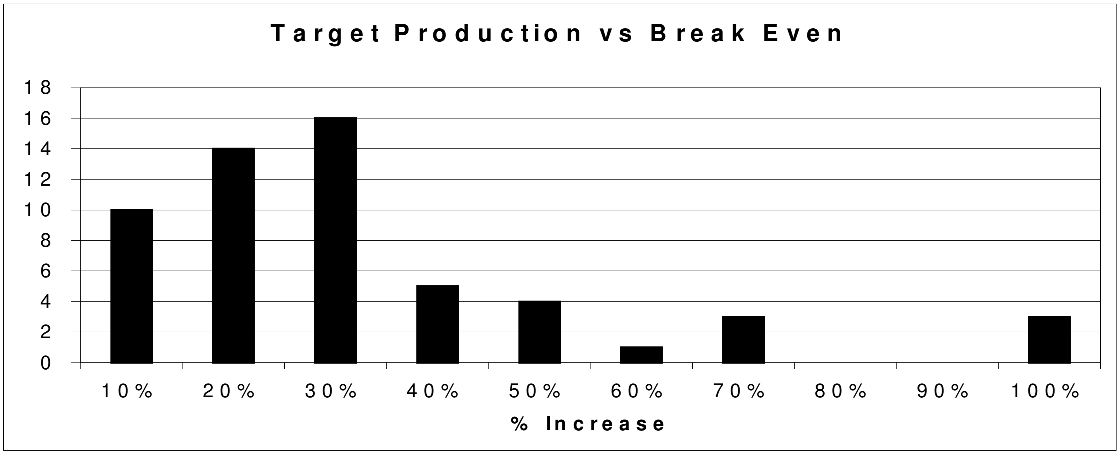

Figure 15. Target production for logging crews stated as additional production over their break-even level.

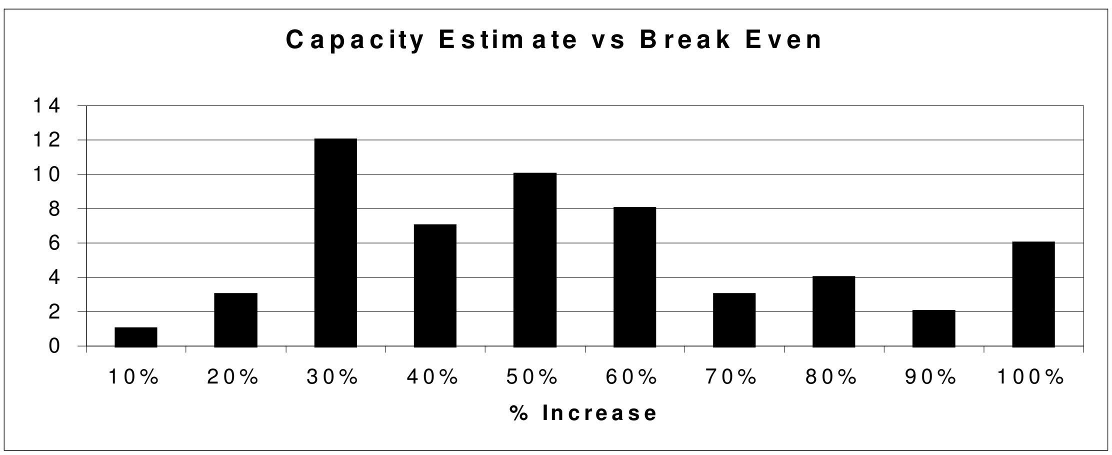

Figure 16. Crew estimates of capacity stated as additional production over their break-even level.

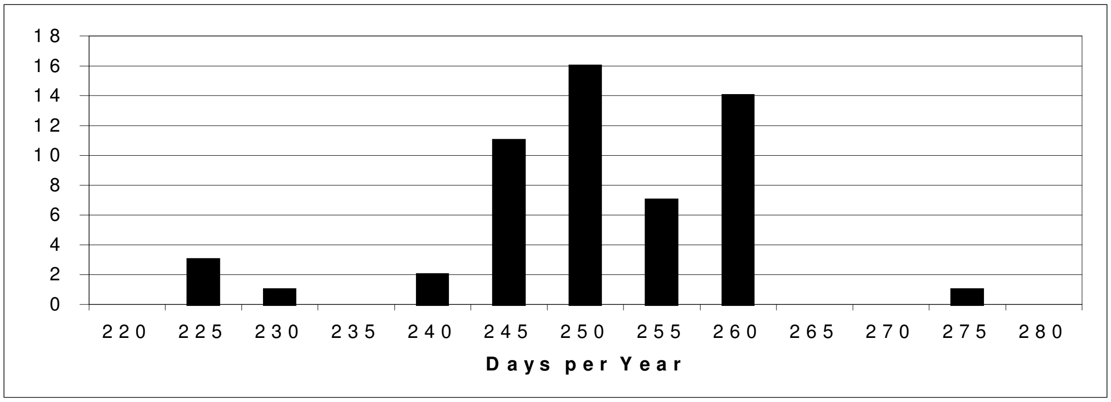

Figure 17. Target operating days per year for logging crews.

About three times as many crews used contractors for some or all of their trucking needs (n=46) compared to those who performed all of their trucking in-house (n=17) (Figure 18). Most businesses were 10-15 years old with nearly all less than 30 years old (Figure 19). These were for the most part established, veteran crews that had been in existence from 5 to 15 years (without considering labor turnover).

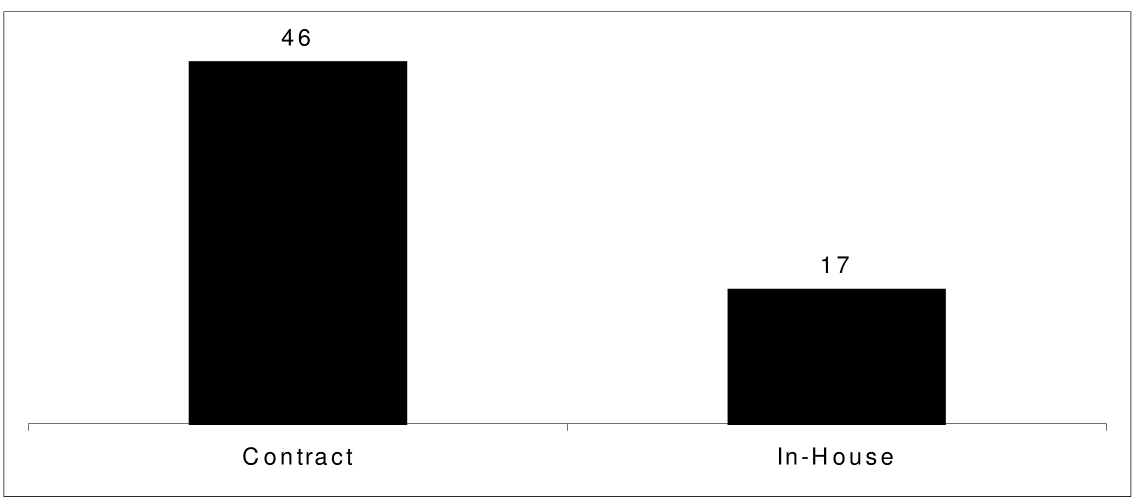

Figure 18. Use of contract trucking or complete in-house trucking by logging crews.

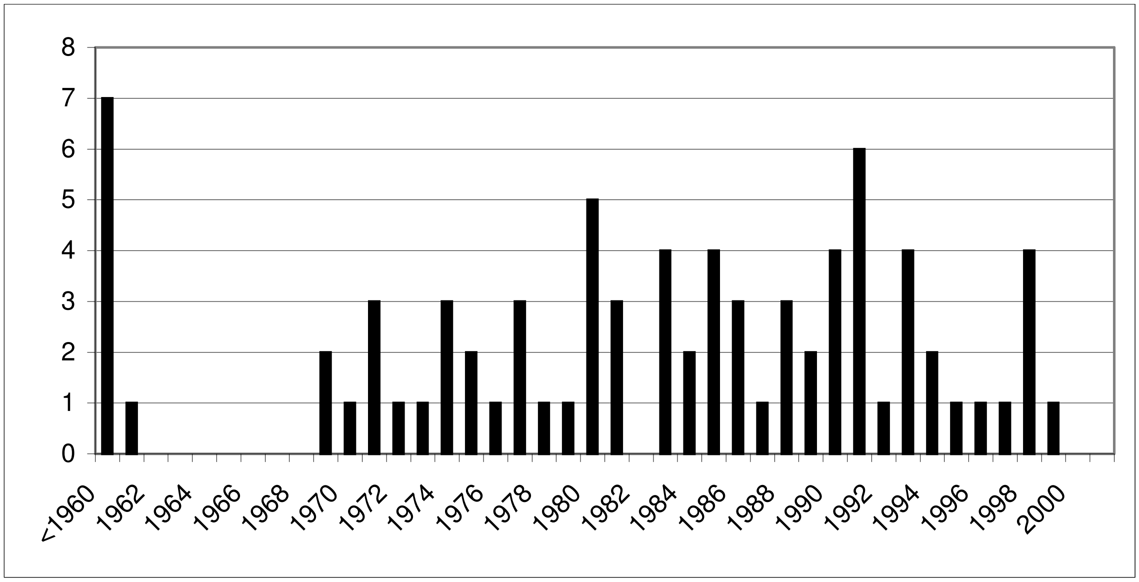

Figure 19. Year of establishment for logging businesses with crews in the study.

Capacity Estimation and Technical Efficiency

During the course of the study, we collected 3,132 logger-weeks of data from 63 logging crews, 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 being used to sever, process, and transport wood did not change significantly during the study. Thus even though there was a time dimension to the information collected, 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 FRONTIER, specialized software to estimate stochastic frontiers (Coelli 1996), I fit the data to a production frontier. The coefficients of the model were significant at the 95% confidence level (Table 1).

Table 1. Coefficients and t-ratios for weekly model, excluding environmental variables.

VARIABLES	Coefficient	t-ratio
Constant	-31.4257	-2.08
ln (capital)	6.8849	18.07
ln (labor)	1.1523	12.5
$(\ln \text{capital})^2$	-0.3848	-17.3
$(\ln \text{labor})^2$	-0.0444	-4.87

99% t-ratio = 2.576

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 was 62.9 %, with a minimum of 4.6 % and a maximum of 96.4 % (Figure 20). 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 additional inputs of K and L will increase output, however, because the coefficients for the squared terms are negative, the production process displays diminishing returns.

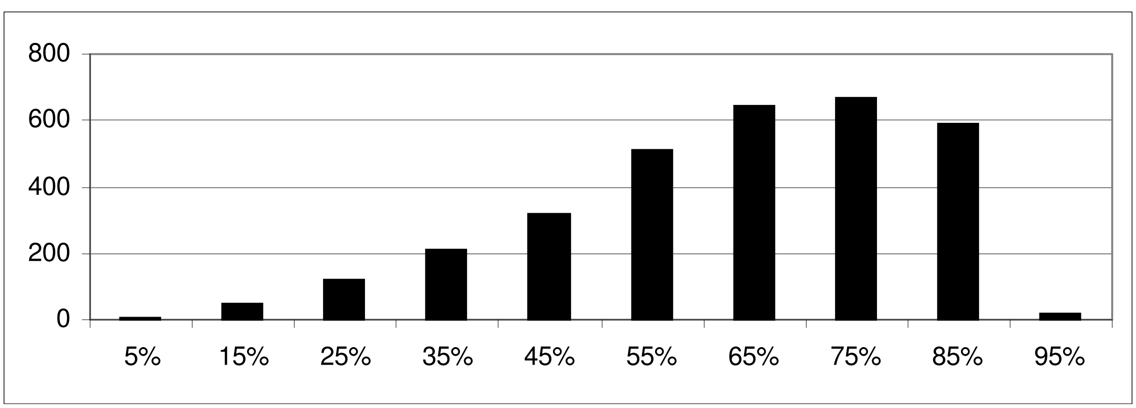

Figure 20. Distribution of efficiency (weekly data).

To test the sensitivity of the output frontier to changes in input values, I used the function to predict the production capacity using the mean values for capital and labor. Then each input was increased and decreased by 10% to track the change in output. Labor caused a greater response in output than capital (Figure 21).

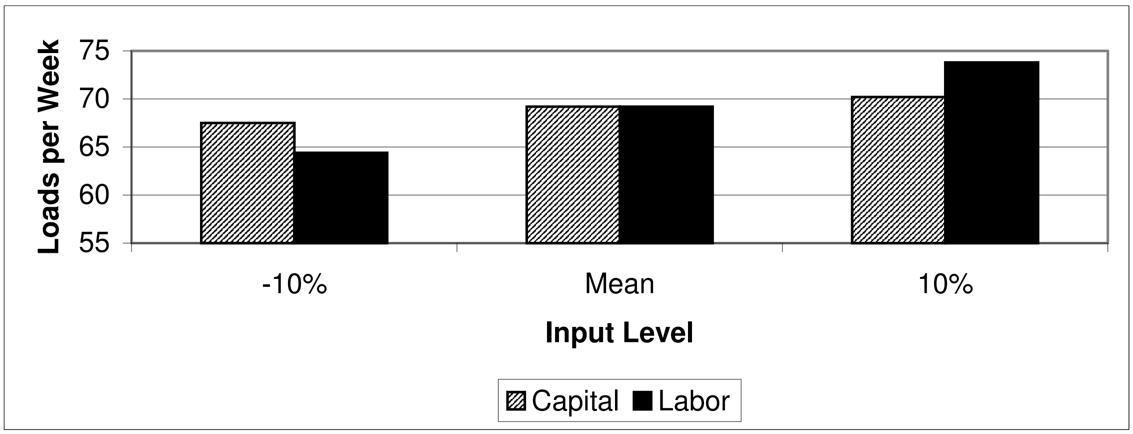

Figure 21. Loads per week, given mean value of inputs and 10 % increase and decrease of each.

Consistent Production

Because the data were collected and expressed in weekly units, concern existed that the frontier would be inordinately influenced 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, the data were collapsed from weekly figures into both monthly and quarterly measures and performed stochastic frontier analysis on the collapsed data sets. To collapse the data, I simply calculated average weekly values of loads hauled and man-hours for each crew by month and quarter. By averaging the data I 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. I expected values for the weekly frontier to be higher than the monthly frontier and the monthly frontier to be higher than the quarterly frontier. A production frontier was fit to the monthly data (n=734). All coefficients were significant at the 95% confidence level (Table 2).

Table 2. Coefficients and t-ratios for monthly model, excluding environmental variables.

VARIABLES	Coefficient	t-ratio
Constant	-22.8494	-6.4
ln (capital)	4.1565	4.1
ln (labor)	2.3657	6.5
$(\ln \text{capital})^2$	-0.2287	-3.9
$(\ln \text{labor})^2$	-0.1558	-4.7

99% t-ratio = 2.576

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 was 65.9 %, with a minimum of 14.6 % and a maximum of 92.9 % (Figure 22).

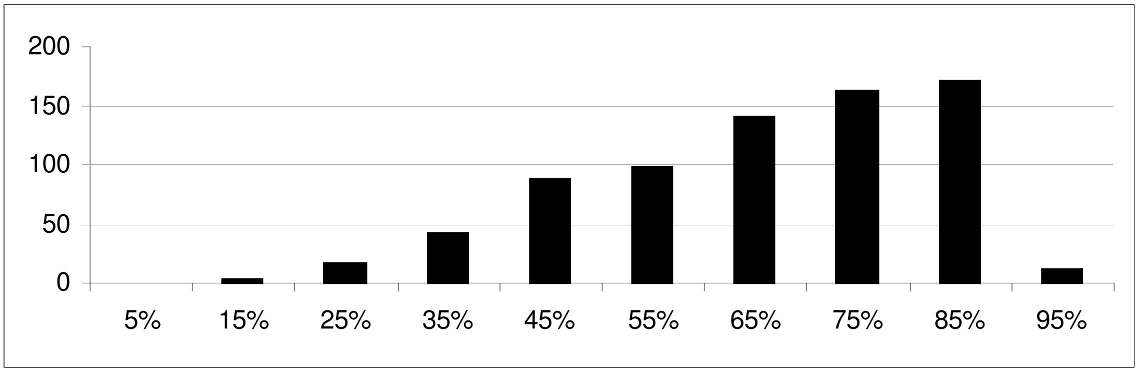

Figure 22. Distribution of efficiency (monthly data).

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. A production frontier was fit to the quarterly data (n=259). All of the coefficients were significant at the 95% confidence level (Table 3).

Table 3. Coefficients and t-ratios for quarterly model, excluding environmental variables.

VARIABLES	Coefficient	t-ratio
Constant	-25.5648	-3.8
ln (capital)	5.0329	2.6
ln (labor)	2.0129	3.1
$(\ln \text{capital})^2$	-0.2802	-2.6
$(\ln \text{labor})^2$	-0.1241	-2.1

99% t-ratio = 2.576

This function yielded production capacity expressed as average weekly production, but determined on a quarterly basis and was unadjusted for environmental variables. Based on this frontier, 259 efficiency scores, one for each observation, were produced. The mean efficiency value was 63.8 %, with a minimum of 15.5 % and a maximum of 92.9 % (Figure 23).

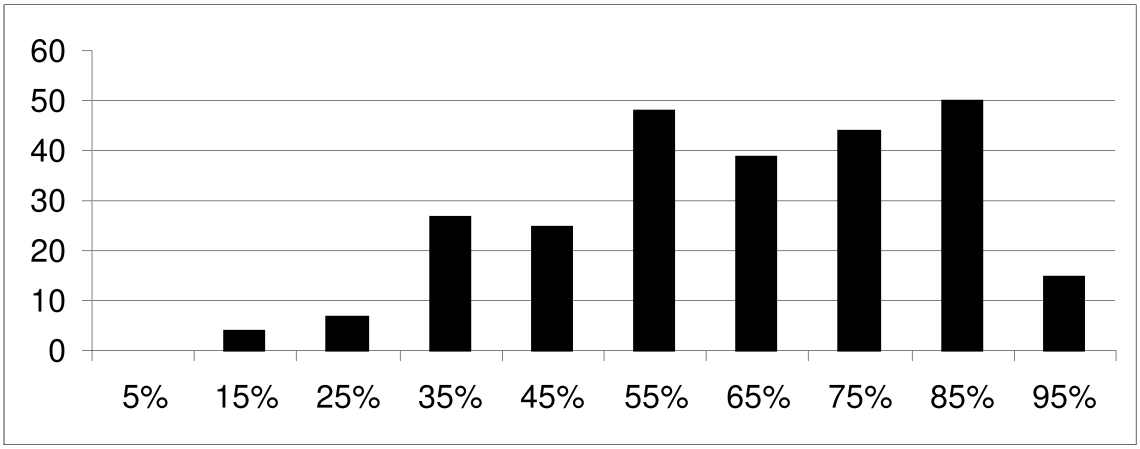

Figure 23. Distribution of efficiency (quarterly data).

There were no heroic-week effects in our data. The mean efficiency actually increased when the data were collapsed by month and quarter as compared to the weekly mean. This seemed to indicate that by collapsing the data, the effects of the poorest weeks were diluted more than any heroic weeks. As a result, the analyses were performed using weekly data.

Environmental Variables

Using the same production data and adding to it the corresponding environmental variables, FRONTIER (Coelli 1996) was used to produce a production frontier, including coefficients that describe the effect of the 14 environmental variables (Table 4).

Table 4. The coefficients of the production frontier, incorporating environmental variables.

VARIABLES		Coefficient	t-ratio
Constant		-5.2577	-2.27
ln (capital)		3.0794	5.046
ln (labor)		-1.8853	-6.48
$(\ln \text{capital})^2$		-0.3020	-7.25
$(\ln \text{labor})^2$		-0.0929	-8.65
(ln labor)*(ln capital)		0.3936	10.7
Preferred Suppier	(0,1)	-0.4687	-12.2
Stumpage via Company	(0,1)	-0.3816	-12.33
Stumpage via Dealer	(0,1)	0.0109	0.21
Partial cut crew	(0,1)	0.8054	27.2
Hardwood Producer	(0,1)	0.4490	13.9
Own Trucking	(0,1)	0.8208	20.22
Age of Business		-0.0102	-4.5
Age of Crew		-0.0027	-1.3
Sells via dealer	(0,1)	-0.4226	-8.8
moves		0.0996	5.4
Piedmont	(0,1)	0.1906	5.6
Mountain	(0,1)	0.4514	9.7
Average haul distance		0.0035	7.25
High Tract rating	(1,2,3)	0.2017	13.8
	$(\text{Sigma})^2$	0.1774	
	gamma	0.7375	
	LLF	-1050.277	
	n	3132	

99% t-ratio =2.576

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 are significant at the approximate 95 percent confidence level. Only ‘stumpage via dealer’ and ‘age of crew’ seem to be statistically insignificant.

As expected, preferred supplier status seemed to reduce inefficiency of the individual crew. This could be due to a more stable level of production, provided 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, again, probably correlated to a more stable production level. Partial cut crews tended to be more inefficient. This was no surprise given the size of the trees being harvested and the care required to remove the harvested trees while not damaging the residual trees. Contractors that were primarily hardwood producers were more inefficient than those that were not. This was probably due to the challenging terrain inherent in hardwood logging operations.

Understandably, many loggers prefer that the liability and expense of trucking be borne by a third party, and it appears that surrendering control of this aspect of the operation increased efficiency. Using age of business as a proxy for experience, it seemed that experience reduces inefficiency. Selling through a dealer tended to decrease inefficiency. This could be due, in part, to the dealer having a variety of outlets where he may sell wood. Moves, as expected, decreased efficiency. Operating in the Piedmont, versus the coastal plain tended to increase inefficiency, and furthermore, operating in the mountains tends to increase inefficiency even more. Average haul distance had a small effect on inefficiency, with increasing distance increasing inefficiency. High tract rating also had an effect on inefficiency. The better the tract rating (closer to 1), the more efficient the crew appeared, conversely, the worse the tract rating (closer to 3), the less efficient the crew appeared.

Effect of Preferred Supplier Status, Dealer Involvement, and Trucking Strategy

To investigate the effects of preferred supplier status, I segregated the predicted efficiency scores from the production inputs only model into two categories: those produced by preferred suppliers (32 crews) and those produced by crews without preferred supplier status (29 crews). The preferred suppliers accounted for 1698 observations. The mean efficiency for crews without preferred supplier status was 61.1%, with a minimum of 4.6 % and a maximum of 96.4 %, while preferred suppliers showed a mean efficiency of 64.6 %, with a minimum of 7.2 % and a maximum of 94.1 % (Figure 24 and Table 5).

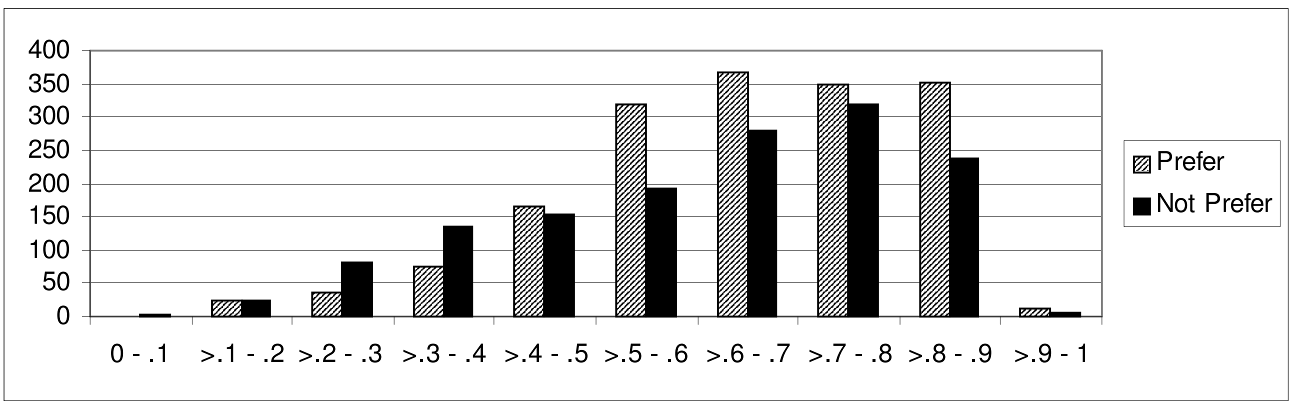

Figure 24. The distribution of efficiency by preferred supplier status (weekly data).

Table 5. Upper quartile, median, and lower quartile of parameters by preferred supplier status.

	Q1	Median	Q3
Without Preferred Supplier Status			
Actual Loads Produced	20.00	42.00	56.00
Capital - Dollars/Week	4517.29	6448.90	7370.96
Manhours/Week	136.00	192.00	270.00
Efficiency	0.48	0.65	0.77
With Preferred Supplier Status			
Actual Loads Produced	35.00	51.00	66.00
Capital - Dollars/Week	5120.25	5984.51	8182.49
Manhours/Week	180.00	244.50	349.80
Efficiency	.55	.66	.78

I used the same method to investigate the effects of dealer involvement. The efficiency scores were segregated into two categories: those that were produced by crews that either received a portion of their stumpage from a dealer or sold a portion of their loads through a dealer (21 crews), and those who had no involvement with a dealer (40 crews). The crews using dealers account for 1228 observations. The mean efficiency for crews without dealer involvement was 59.5 %, with a minimum of 4.6% and a maximum of 94.7 %, while those crews utilizing dealer relations possessed a mean efficiency of 68.4 %, with a minimum of 10.5 % and a maximum of 96.4% (Figure 25 and Table 6).

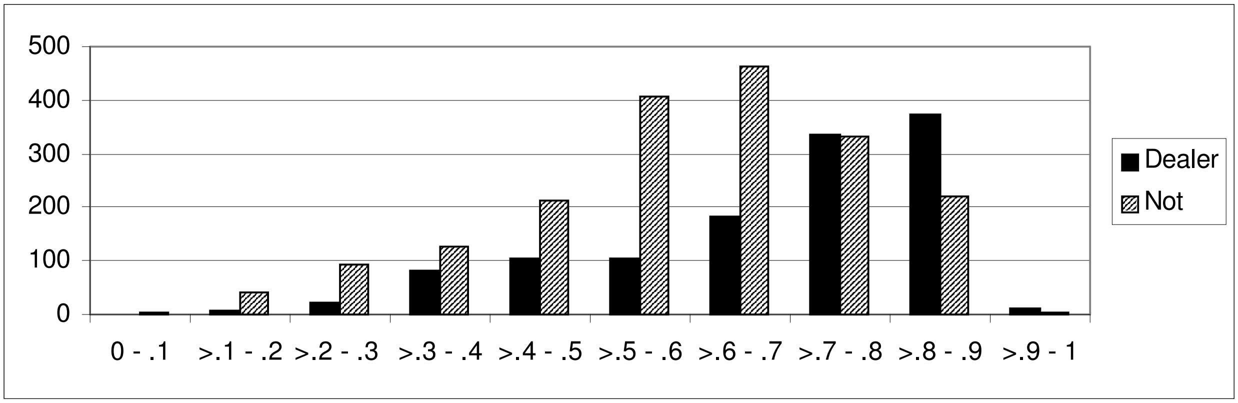

Figure 25. Distribution of efficiency by dealer involvement (weekly data).

Table 6. Upper quartile, median, and lower quartile of parameters by dealer involvement.

	Q1	Median	Q3
Without Dealer Involvement			
Actual Loads Produced	24.00	45.00	58.00
Capital - Dollars/Week	4517.29	5550.01	7919.31
Manhours/Week	168.00	246.00	346.00
Efficiency	0.50	0.61	0.72
With Dealer Involvement			
Actual Loads Produced	34.50	50.00	65.00
Capital - Dollars/Week	4671.48	5984.51	8182.49
Manhours/Week	142.50	200.00	255.00
Efficiency	0.59	0.74	0.81

Again, I divided the predicted efficiencies into two categories. One category included crews that indicated they primarily relied on their own trucks for hauling wood (23 crews). The other category was crews that indicated that they use some mix of their own trucks and contract trucks (38 crews). Crews performing their own trucking account for 1232 observations. Crews that haul their own wood had a mean efficiency of 62.2 % with a minimum of 10.5 % and a maximum of 91.3 % (Figure 26 & and Table 7).

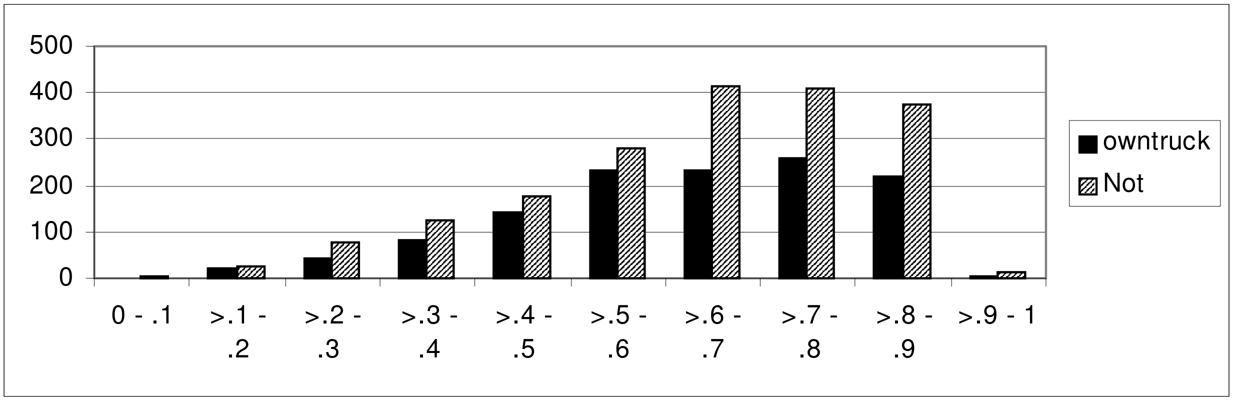

Figure 26. Distribution of efficiency by trucking strategy (weekly data).

Table 7. Upper quartile, median, and lower quartile of parameters by trucking strategy.

	Q1	Median	Q3
Using Contract Trucks			
Actual Loads Produced	31.00	47.00	61.00
Capital - Dollars/Week	5035.80	6649.08	9645.69
Manhours/Week	161.00	216.00	288.00
Efficiency	0.53	0.66	0.78
Using Own Trucks			
Actual Loads Produced	23.00	46.00	61.00
Capital - Dollars/Week	4138.85	5314.91	6555.83
Manhours/Week	136.00	215.00	350.25
Efficiency	0.51	0.64	0.77

Application

To illustrate an application of this method of estimating logging production capacity, consider a hypothetical logging crew that uses a feller-buncher, two skidders, a loader, and employs five men. The target workweek is five days of eight hours, translating into 200 man-hours per week. The capital index is $5,651 per week (Table 8). Assume the crew averages 50 loads of wood hauled to the mill per week. The inputs for the model are the natural logarithm transformations of 200 man-hours per week and $5,651 per week.

Table 8. An illustration of the calculations of the capital index.

	Fixed Cost		Variable Cost	Total Cost
Equipment	Per year	Per SMH	Per SMH	Per SMH
Feller-buncher	$47,813	$23.91	$33.00	$56.91
Skidder	$34,345	$17.17	$12.00	$29.17
Skidder	$34,345	$17.17	$12.00	$29.17
Loader	$30,414	$15.21	$10.81	$26.02
Total per SMH				$141.27
times SMH per week				40
Total Capital Estimate per Week				$5,650.74

Assumes 2000 SMH per year.

Applying the natural logarithm of $5,651 per week (8.639588) and the natural logarithm of 200 man-hours (5.298317) to the weekly model gives the natural logarithm of weekly load capacity, or the capacity benchmark for this crew as follows:

$$4.19342 = -31.4257 + 6.8849 * (8.559946) + 1.1523*(5.298317) - .3848*(8.559946^2) - .0444*(5.298317^2)$$

Taking the antilogarithm of 4.19342 gives 66.2 loads per week. This is the productive capacity of this hypothetical crew as determined by the estimated production frontier and our list of assumptions. Since our crew averages an actual production of 50 loads per week, we estimate this crew is 75.5 % efficient (50/66.2), or 24.5 % inefficient.

CHAPTER 5

SUMMARY, CONCLUSIONS, AND POLICY IMPLICATIONS

The performance of logging crews in the wood supply system in the southern United States and Maine was examined. To gauge performance, I used efficiency. Efficiency is a common measure by which firms of all types judge their performance. Specifically, I used technical efficiency, which is simply the ratio of output produced to a benchmarked capacity for a given level of inputs. The number of loads hauled to the mill each week served as output. Total number of man-hours and weekly operating expense provided measures of input.

I used stochastic frontier analysis to estimate logging capacity based on the data that we collected. From this benchmark, technical efficiency scores were calculated. Based on weekly data, I estimated the timber harvesting force in the southern United States and Maine to have been operating at approximately 63% efficiency.

Factors other than capital and labor also affect efficiency. Fourteen environmental variables were examined to understand their effect on efficiency. Twelve of the fourteen variables were significantly associated with efficiency, either positively or negatively, at the 99% confidence level. Most notably, the loggers that were preferred suppliers to some mill tended to have higher efficiency scores. This is likely due to the relative stability in production that these logging crews enjoy. Crews that use primarily their own trucking tended to have lower technical efficiency scores than those who Used contract trucking. This is likely due to reduced flexibility in times of high demand.

The finding that output is more responsive to a change in labor than in capital seems counterintuitive, given that the prevailing trend is to replace men on the ground with machinery. The logging industry has undergone an approximate 30-year period of mechanization. Many factors have contributed to the mechanization of the industry, such as increased productivity associated with machinery, increased safety associated with putting men in machines and keeping them off of the ground and the resultant cost savings in insurance due to the increased safety. It seems now, however, that with the current technology, many logging crew managers have scaled back their labor force, in favor of capital-intensive operations to the point that a pair of human hands provide more return on investment, in terms of productivity, than would an investment in machinery of the same magnitude.

These findings suggest that there exists some opportunity to improve wood flow efficiency by up to nearly 40%. It is well understood that this supply chain of wood will likely never be 100% efficient, regardless of the amount of research undertaken, the amount of cooperation extended between logger and mill, or the increased reliability of wood transit. There will always be the effects of weather, the occasional wild market swing, and plain old luck plaguing this industry and many others, but there is room for improvement.

A procurement manger may read these findings as interesting, but hardly his/her problem. It may not be immediately recognizable, but inefficiency in a supply chain affects all the links in the chain to some extent. This notion has been proven time and again in management science. The cost of inefficiency is borne by the system. The loggers may bear this cost initially, but as time presses on and the invisible hand of economics manipulates the markets, the cost can revert back to the mills in many forms including shortage. This warning holds little threat given the current state of over capacity in the logging industry, but during the course of just this study, many loggers have scaled back or turned to other occupations. Many still argue that the cost will simply be passed along to the end consumer of finished goods, but in an ever-increasingly global marketplace, the assumption that "Americans buy American" is losing potency. To the procurement manger I would suggest that it is in the long-term interest of his/her company to improve the efficiency of the supply chain of wood. The implementation of some form of preferred supplier system is under the control of the purchasing side of the table and certainly appears to be effective at reducing inefficiency by providing a stable, predictable market. Loggers in these systems can tailor their operation more to this level of production, rather than being forced to maintain reserve capacity to take advantage of the "feast" in their "feast or famine" occupation.

There are also steps that logging firms can take to improve their efficiency. If they do not utilize contract trucking, they should evaluate their fixed costs of maintaining a trucking fleet versus the added flexibility of creating a relationship with contract trucking source. Are they a preferred supplier? Do they view the mill as the enemy, rather than a customer? Logging firms should take the initiative to push for preferred supplier status and be willing to negotiate for a stable market place.

A properly functioning preferred supplier system will inevitably drive the low performing logging contractors away from logging. This is the cold, hard fact of economics. There is a level of demand for wood that exists. There are enough loggers to produce about 40% more wood than is demanded. The preferred supplier system will reward the higher performing contractors with a stable market, typically at the cost of lower cut-and-haul rates, by dispersing the demand through a smaller number of contractors. The discrepancy in price is reclaimed via increased output and better tailored operations that have lower costs and higher efficiency. The logging firms have the incentive and ability to produce, with the responsibility to the mill of producing a stable supply of wood and adhering to the mill's policies such as safety compliance and tract condition following harvest. The mill has the incentive of a stable supply of wood from a smaller, easier-to-manage group of logging contractors at a reduced price. The mill also has the responsibility to the loggers of providing a stable market and monitoring the group of loggers, stripping preferred supplier status from those contractors who do not comply, and awarding it to loggers that show potential.

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APPENDICES

Appendix A

1. Logger Profile Instructions and Form
2. Weekly Logger Report Instructions and Form

INSTRUCTIONS

(Rev. 3-31-2000)
Participant Information Form

Contact Information: Please provide this so that we can contact you if questions arise about data that you provide and to allow us to mail periodic updates or newsletters to you about the progress of the study. Your information will be entered into a database without your name or contact information.

Owner Names & Information: This is demographic data that will be used to characterize participants in the study.

Labor Information: This information will allow us to get an idea of the amount of labor required per unit of production. In addition, the age and time in position for each employee will give us an idea of experience level and maturity. Include truck drivers that drive highway trucks that you own and operate.

Equipment Spread: Provide this information for each piece of logging equipment used on your crew on a regular basis. If spare equipment is maintained, list these and indicate (spare) under the type column. Include log trucks that you own and operate.

Preferred Supplier: If you are a preferred supplier (often called a key or core supplier) of a mill with a formal program of this type, answer yes and indicate the name of the mill.

Business Type: Indicate how your business is organized legally.

Stumpage Source: Indicate your primary source of stumpage. If you purchase most of your wood with your own funds, indicate ***independent***. If you primarily cut timber from company lands or on land where the timber has been purchased by a market company, indicate ***company***. If you deliver wood to a market through a wood dealer or supplier that supplies the stumpage, indicate ***dealer***.

Market Access: If you deal directly with a market company or companies, indicate ***direct***. If you deliver wood to markets through a wood dealer or supplier, indicate ***dealer***.

Harvest Percentages: Use percentages to indicate the types of products produced (chips or roundwood), types of harvests (clearcuts, thinnings, or diameter limit or partial cuts), and species (pine or hardwood). The percentages on each line should total 100%.

Production Capacity: How many loads per week could you produce if on a reasonably good tract and did not face market restrictions such as quotas? Give a production number that you could sustain for several weeks, not a short term peak production requiring a lot of overtime that could not be maintained for long. This should be a production level that you do not often reach. If possible, provide the answer in both loads and tons.

Target Weekly Production: When not facing quotas, what is your target production level? How much do you want to produce to feel that you have had a decent week? This estimate should be closer to your average production than the production capacity indicated above. If possible, provide the answer in both loads and tons.

Break-Even Production Level: How many loads do you feel you need to produce each week to financially break-even (no profit or loss)? If possible, provide the answer in both loads and tons.

Target Work Week and Work Year: Indicate your planned normal work week in hours/day and days/week. How many weeks per year do you plan to work?

Trucking Method: Indicate if you contract for all of your trucking, if you own all of your trucks, or if you own some and contract for the remainder.

Number of Product Sorts: Indicate the number of sorts that you typically make.

Mill Information: Give the product, company, and location for each mill where you deliver wood. Indicate if this is typically hauled by yourself or others. If the person hauling the wood varies depending on truck availability, leave this column blank.

LOGGER PROFILE FORM (Rev 3-31-2000) Confidential Research Record

Business Name ______________________ Year Established ____________

Crew Name or #: ______________________ Year Established ____________

Address ____________ City ______________ State ________ Zip ________

(Office) (   ) ______________ (Mobile) (   ) ______________ Email: ____________

(Home) (   ) ______________ (Fax) (   ) ______________

Owner Names	Age	Year hired	Became Owner (year)	Education

Employees (include truck drivers who are employees)

Position Title	Age	Year Hired	Employee Name	Other duties	Time @ position

Crew Equipment Owned (include owned haul trucks and trailers)

Type	Make	Model #	Model Year	Year Purchased

Is this crew a preferred supplier of any mill		Yes (name)	________	No	________
Business Type Limited Liability Corp	________	Sole Proprietorship	________	Partnership	________
S-corporation	________	C-corporation	________		
Stumpage Source Company	________	Independent	________	Dealer	________
Market Access		Direct	________	Dealer	________
Annual harvest percentages Chips	________	Roundwood	________		
(each line should total 100% Thinning	________	Clearcut	________	Dia Limit	________
Pine	________	Hardwood	________		

What is the productive capacity of the operation	Total Loads / Week	________	Total Tons	________
What is the target (goal) production of the operation	Total Loads / Week	________	Total Tons	________
What is the break-even level of the operation	Total Loads / Week	________	Total Tons	________
What is the target work week	Days / Week	________	Hours / Day	________
How many days or weeks per year do you plan to work	Weeks / Year	________	Days/Year	________

Predominant trucking method Contract ________ Company ________ Mix ________

How many product sorts are typically made ________

Mill information - List all potential markets

Product	Destination Company (include City, State)	Hauled by	
		Self	Other
		Self	Other
		Self	Other
		Self	Other
		Self	Other
		Self	Other
		Self	Other
		Self	Other
		Self	Other
		Self	Other

INSTRUCTIONS
Weekly Production Report for Loggers

Production Information: List product (pine pulpwood, hdwd sawtimber, etc.), mill destination (company, location), mileage from woods, and number of loads each day.

Additional Potential Loads Missed Due To: Carefully consider the production that you achieved and indicate if you feel that additional loads could have been produced. Indicate the number of additional loads that could have been produced each day if one of the factors in *italics* had not happened. You should be relatively confident of the number of loads missed and the cause before you record this. For a detailed explanation of these causes, see the attached descriptions.

Number of People on Site: Indicate the number of people in the woods working during the day.

Total Hours Worked: How many hours was the crew paid for or were on site?

Total Hours Logging: These should be time working, excluding travel to the site, lunch and breaks, extended equipment downtime, etc.

Loads Hauled by Your Trucks: Number of loads hauled that day by trucks you own and operate with your employees.

Loads Hauled by Contract Trucks: Number of loaded hauled by contracted trucks.

Number of Product Sorts Made: How many different products were you sorting out of the wood harvested for delivery to different markets?

Number of and Reasons for Moves: Indicate if the crew moved from one tract to another on a given day and indicate the reason for the move using the attached list.

Daily Tract Rating: Rate the logging conditions on this tract as Good (above average or better than expected), ***Fair*** (pretty typical), or ***Poor*** (worse than usual or expected). This could vary day by day given weather, variable stand conditions across a sale, etc.

Lost Production Codes

Market / Quota – Production lost due to direct or indirect results of quota or wood order constraints. Examples may include lost utilization of in-woods assets created by low demand for quota products, lost utilization of transport vehicles loaded with quota products, increased hauling distances to markets that are only used when wood orders at primary markets are restricted, moves forced by restricted wood orders, loss of landing or deck inventory space occupied by products on quota, complete shutdown of operations when wood orders are filled, etc.

Market / Mill Closed – Lost production created by an unplanned or short-notice closure of receiving mill. Examples may include idling of in woods operation until mill re-opens, loss of deck inventory space created by stockpiling of unmarketable products, trucking asset tie-ups, etc.

Market / Handling – Production lost to inefficient unloading or handling of product. Examples may include extended turn times while in mill, unloading problems, lack of inventory space, handling equipment breakdowns or capacity, etc.

Regulations / Mandatory – Production lost as a direct result of complying with mandatory regulations for the operation, state or local ordinances. Examples may include mandatory BMP's, DOT inspections, DOT scales, random drug testing, posted roads, DEP mandatory compliance orders, mandatory licensing and training time, etc. *(For the purposes of this study it should be assumed that mandatory regulations are a fact of life. This lost production cause should be used when the time spent to comply competes directly with productive activities that were otherwise scheduled. Compliance activities which reasonably could have or should have been addressed during times or in ways that did not compete with production should not be charged).*

Regulations / Voluntary – Production lost from complying with voluntary standards. Examples may include activities associated with voluntary BMP's (seeding, mulching, placing water control structures, efforts to enhance aesthetics,…) and certification or "training" associated with voluntary programs like SFI.

Mechanical / Scheduled – Production lost due to scheduled maintenance tasks. Examples may include preventive maintenance / service, routine overhauls, warranty work, product updates, replacement of wear items such as tires, cables, chains, undercarriages, etc.

Mechanical / Unscheduled – Production lost to any unplanned / unscheduled repair item. Examples may include equipment breakdown from normal wear, abuse, vandalism, accidents, cold weather problems, seasonal problems, and wear items not identified in routine maintenance.

Labor / Amount – Production lost due to lack of labor. Examples may include excused or unexcused absence, injury, early leave or late arrival of employees, inability to find and hire willing employees, etc.

Labor / Quality – Production lost as a result of available labor that is not productive or efficient. Examples may include the learning curve of new hires, inexperienced personnel, workers unwilling to operate within guidelines, workers who through inexperience or other reasons hinder the productive capacity of the operation.

Weather / Roads – Production lost due to roads that are unable to support harvesting traffic. Examples may include roads that are not passable due to snow, mud, debris, or damage, roads not used in an attempt to prevent further damage, etc. *(Weather should not be charged as a cause if there is a reasonable planning action, which could have been taken to avoid the reduced productivity or downtime).*

Weather / Woods – Production lost due to factors once in the woods that are dangerous or counterproductive to the operation. Examples may include wind, deep snow, excessive mud / rutting, heavy rain, excessive thawing, electrical storms, etc. *(Weather should not be charged as a cause if there is a reasonable planning action which could have been taken to avoid the reduced productivity or downtime).*

Planning Errors *– Production lost to obvious and avoidable errors in planning by one or more parties involved in the process. In selecting from the following list of planning errors you are asked to seriously consider whether or not there was a reasonable action that could have been taken to make things run more smoothly.*

Planning / Stumpage – Production lost due to poor procurement of stumpage. Examples may include no stumpage bought, other availability issues that created insufficient lead-time for an efficient startup and operation, etc.

Planning / Access – production lost due to lack of access to stumpage. Examples may include lack of right of way to stumpage, dispute of right of way to stumpage, access that has not been built or adequately prepared, terrain or ownership patterns that confine the working area or capability of the operation that could have been addressed

Planning / Harvest – production lost due to harvest planning work not being complete or poorly done. Examples may include boundaries not identified, a generally poor logging plan or no logging plan, critical skidding patterns or trails not planned, landing not identified.

Planning / Woods Equipment / System – Production lost due to mismatch / limitations of woods equipment. Examples may include timber type / size not matched with system, terrain that is too wet, steep, or rocky for equipment on hand, tract layout not suited to system capabilities such as long, steep, skid adverse turns, etc.

Planning / Transporting Equipment / System – Production lost from inability of transportation equipment to adequately move material once it has arrived at the landing. Examples may include timber size type not matched with trucking capacities, haul distance exceeds capacity of available system, available truck configurations not matched to the particular job (road quality, width, curves, grades, turnouts, etc.)

Stand & Tract Issues - Production losses related to timber type, volume, or other physical limitations that are not necessarily the result of poor planning or manageable with better planning.

Vacation – Production lost due to idling of all or part of the crew for planned vacations or holidays. (Planned vacations supercede labor / amount as the reason for lost production).

Reasons for Tract Moves

CP – harvesting of the entire sale unit has been completed and no additional harvest activity is necessary

BO – a better business opportunity presented itself while tract was being cut. Examples of this can be a better product mix for the operation, better haul, better price / cash flow option

PQ – product quota forced operation to relocate because product mix on tract does not match market needs

RF – failure of haul road to support trucking through road breakdown

WF – failure of in woods conditions to support machine traffic

SR – saving a "relief" portion of a sale for a more adverse time. Examples may include leaving high operability sites until needed, saving high value sites until market demands meet requirements, saving areas not traditionally affected by quota

PC – previous commitment that forces an operation to move. Examples may be tracts that are now operable but were not previously, short time frame for harvesting site, cleanup of previously harvested sites, expiring contracts.

OT – other factors not listed above

Weekly Production Report for Loggers

Confidential Research Record

Rev. 3-31-2000

Logger Name ____________________ Crew ___________ Week Ending _____________

		Miles	Number of Loads							
Product	Destination	to Mill	Mon	Tues	Wed	Thurs	Fri	Sat	Sun	Total
TOTAL LOADS										
TOTAL TONS - (optional)										
Additional Potential Loads Missed Due To:										
Market / Quota										
Market / Mill Closed										
Market / Handling										
Regulations / Mandatory										
Regulations / Voluntary										
Mechanical / Scheduled										
Mechanical / Unscheduled										
Labor / Amount										
Labor / Quality										
Weather / Roads										
Weather / Woods										
Planning / Stumpage										
Planning / Access										
Planning / Harvest										
Planning / Woods Equipment										
Planning / Transport Equipment										
Stand / Tract Issues										
Vacation										
Number of people on site										
TOTAL HOURS WORKED										
TOTAL HOURS LOGGING										
Loads Hauled by Your Trucks										
Loads Hauled by Contracted Trucks										
Number of Product Sorts Made										
Number of Moves										
Reasons for Move (see instructions)										
Daily Tract Rating (see instructions)										

Appendix B

1. Fixed Cost and Operating Cost Calculations
2. Average Cost by Equipment Category

Fixed Cost and Operating Cost Calculations

I. Fixed Cost per Year = Depreciation + Interest + Insurance

1. Depreciation = (Purchase price – Salvage value)/Expected life of machine
   a. Salvage value = Purchase price * Salvage Percentage
2. Interest = Interest Rate * Average yearly investment
   b. Average Yearly Investment = {[(Purchase Price – Salvage Value) * (Expected Life +1)]/(2 * Expected Life)} + Salvage Value
3. Insurance = Purchase Price * Insurance and Tax Rate

II. Operating Cost Per Scheduled Machine Hour = Operating Cost Per Production Machine Hour * Utilization Rate

1. Operating Cost per Production Machine Hour = (Repair & Maintenance + Lube & Oil + Fuel) / PMH
2. Repair & Maintenance = (R&M Rate * Depreciation) / Productive Hours per year

Average Cost By Category

	Fixed Cost Per Year	Operating Cost Per Scheduled Machine Hour
Chipper	$61,325.01	$32.65
Delimber	$6,647.91	$2.03
Feller	$47,813.15	$16.67
Track Feller	$68,291.07	$19.41
Forwarder	$52,157.93	$20.36
Harvester	$115,614.71	$38.48
Track Loader	$67,978.24	$21.18
Loader	$30,414.11	$10.81
Skidder	$34,344.98	$11.81
Track Skidder	$63,858.24	$18.82