AN ABSTRACT OF THE THESIS OF

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Title: An Analysis of Technical Efficiency and Productivity Growth in the Pacific Northwest Sawmill Industry

Abstract approved:

Darius M. Adams

The objective of this project was to investigate technical efficiency and productivity growth in the Pacific Northwest sawmilling industry over the period 1968-2002. Productivity growth was decomposed into three components: technical change, efficiency change, and scale efficiency change. In addition, using econometric methods, changes in output elasticities and input substitution elasticities were examined.

Chapter 2: In an analysis of the Washington state sawmilling industry, data envelopment analysis (DEA) was employed to examine the technical and scale efficiency of the sawmill industry. Technical efficiency was found to vary on both a regional and temporal basis. For most years the industry (in aggregate) operated at a point of modest scale inefficiency. The industry's rates of productivity growth and technical change were examined using the

Malmquist input-oriented productivity index. The results of this analysis indicate that the industry experienced modest average annual *declines* in productivity and technical change during the 1970s, but experienced strong productivity growth and technical change during the 1980s and 1990s.

Chapter 3: In an analysis of the Oregon and Washington sawmilling industry, stochastic frontier analysis (SFA) was employed to examine productivity growth and the components of productivity growth: technical change, efficiency change, and scale efficiency change. The results of this analysis indicate that productivity growth was strong over the 30-year study period. Productivity growth was found to be due almost exclusively to technical progress. Efficiency change was found to be very small and *negative* throughout the study period and scale efficiency change was found to be very small, but positive during the 1990s and zero in earlier years. Morishima input substitution elasticities, were found to vary over the study period.

Chapter 4: In an analysis of the Oregon and Washington sawmilling industry, technical and scale efficiency were examined using data envelopment analysis (DEA). Productivity growth and its decomposition were also examined using the Malmquist productivity index. Following the methods described by Simar and Wilson (1998, 1999, 2000a, 2000b, 2002), the smoothed bootstrap technique was used to construct confidence intervals for the technical efficiencies and Malmquist productivity indices. The results of this study were compared to the results obtained in Chapter 3. Consistency was found between the results of Chapters 3 and 4 with respect to the direction of productivity growth and technical and efficiency change. However, the two methods differed considerably in their estimates of the rates of productivity growth and technical change. The results of both chapters indicate that productivity growth in the Northwest sawmilling industry was driven primarily by technical progress.

An Analysis of Technical Efficiency and Productivity Growth in the Pacific Northwest Sawmill Industry

by

Ted L. Helvoigt

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APPROVED:

Major Professor, Representing Forest Resources

Head of the Department of Forest Resources

Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Ted L. Helvoigt, Author

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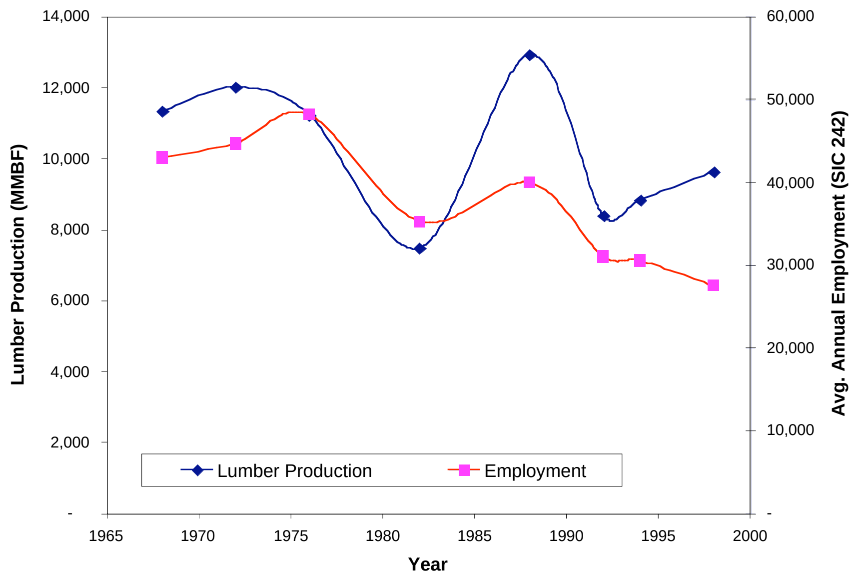
INTRODUCTION

Although its relative shares of the Oregon and Washington economies have slowly declined over the past decades, the forest products industry in the Northwest continues to be a major source of employment and economic output. Changes in timber supply from private and public lands and ever increasing competition from lumber manufacturers in other regions of North America and abroad have resulted in an industry that looks much different today than it did 30 years ago. There are fewer sawmills in the Northwest today. Mills are larger, more automated, and, based on anecdotal evidence, more productive. Over the past decade, the share of logs harvested from Northwest forest and processed by the region's sawmills has increased as log exports (to Asia) have dramatically declined and many of the region's veneer and plywood mills have closed. Today sawmills are by far the largest consumers of Northwest logs.

Because of its historic and continued importance to the economy of the Northwest and its particular importance to individual communities in the Northwest, it is important to understand how the structure of the forest products industry has changed in recent decades. The purpose of this study is to examine the production structure of the Northwest forest products industry and how it has changed over the past three decades. The results of this analysis should prove valuable to the public and policy makers in the Northwest, as well as decision makers within the forest products industry.

The sawmilling industry of the Pacific Northwest experienced substantial swings in lumber production between the early 1970s and late 1990s (see Figure 1). Lumber output dropped substantially between the mid-1970s and the early 1980s, due in large part to the national recession. As the national economy grew out of the recession, lumber production soared, increasing by more than 50% between 1982 and 1988. However, the increased production was short lived. Due to national concerns about rapid loss of old growth forests in the Northwest and the 1990 listing of the spotted owl as a threatened species (under the Endangered Species Act), lumber production in the Northwest dropped precipitously. Bottoming out in the early 1990s, lumber production in the Northwest has grown relatively slowly since.

Figure 1: Northwest Sawmill Employment and Lumber Production, 1968-1998



Source: Oregon and Washington mill survey data

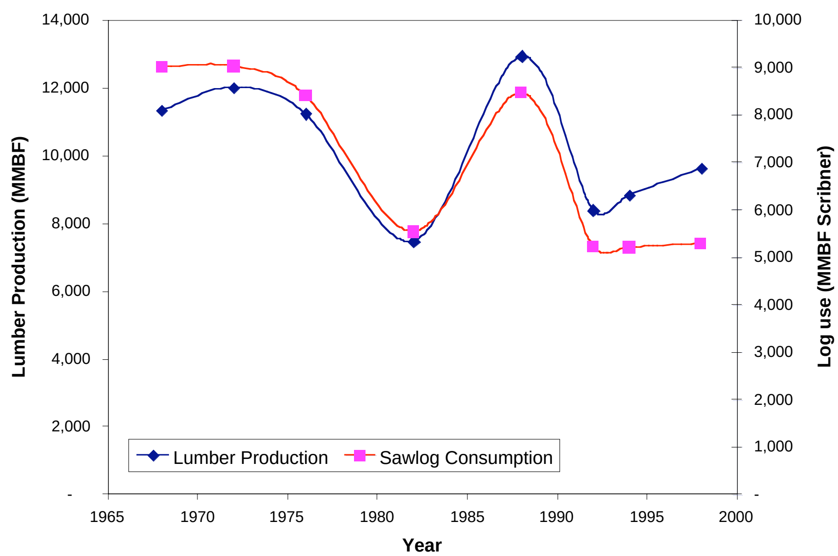
The relationship between lumber production and sawmilling employment (SIC 242) began to diverge in the 1980s. As lumber production spiked in the mid-1980s, employment grew only modestly, and as production grew through the mid-1990s, employment continued to decline.

Over this same period, a similar but not nearly so extreme relationship existed between lumber production and log use (see Figure 2). Log use and lumber production track very closely throughout the study period. However the quantity of logs necessary to produce a given amount of lumber continued to decreased between 1968 and 1998.[1] This is most apparent after 1992. As lumber production increased through the mid 1990s, it did so with

[1] Note that log use is measured in Scribner, not in cubic meters. Average log diameter has decreased substantially between the early 1970s and late 1990s and Scribner is widely criticized for under-measurement of smaller sawlogs.

progressively less (Scribner) log volume. On an average annual basis, lumber production per MBF of sawlog input increased by approximately 1.2% in the Northwest. The rate of growth in lumber production per MBF of sawlog differed for westside (1.3% per year) and eastside mills (0.8% per year). Westside lumber production as a percentage of total Northwest lumber production grew from 75% in 1968 to 85% in 1998.

Figure 2: Log Use and Lumber Production, 1968-2002

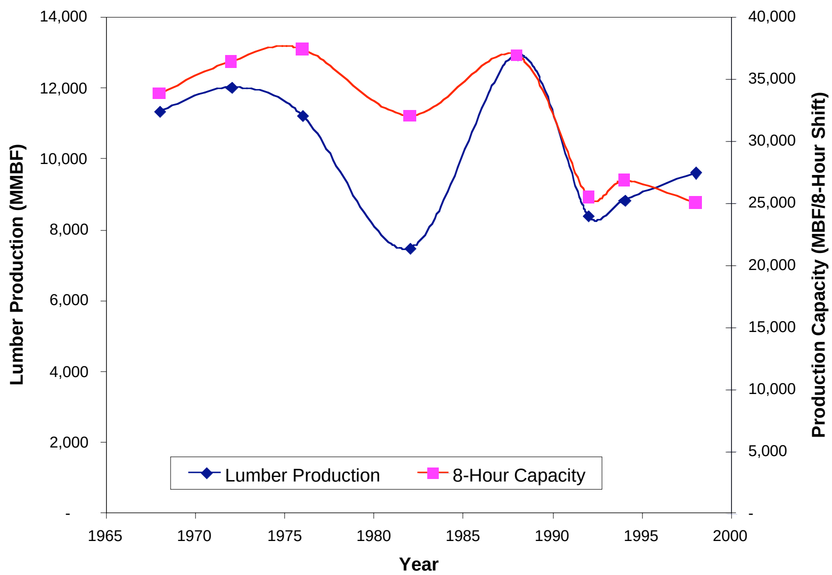


Source: Oregon and Washington mill survey data

Through the 1970s and early 1980s, capacity did not rapidly adjust to declining lumber production. This is not an unreasonable finding, as one would expect a delayed response in the adjustment of capital stock to a change in lumber production. Likely, many producers believed that lower demand for their lumber would be temporary and so adjusted their use of variable inputs (e.g. unskilled labor), but did not adjust their lumber-producing capacity. Milling capacity in the Northwest did dip in the late 1970s and early 1980s, likely due to the least economically efficient mills closing.

The impact on lumber capacity to declining log volumes and lumber production in the late 1980s and early 1990s was very different. The flow of logs from federal forests declined rapidly beginning in the late 1980s and has never recovered. Perhaps (correctly) believing that log flows from federal forests would not recover, lumber-producing capacity dropped precipitously over this period as the mills throughout the Northwest most reliant on federal timber permanently shut down. Milling capacity has remained relatively stable since the early 1990s, even as lumber production has grown.

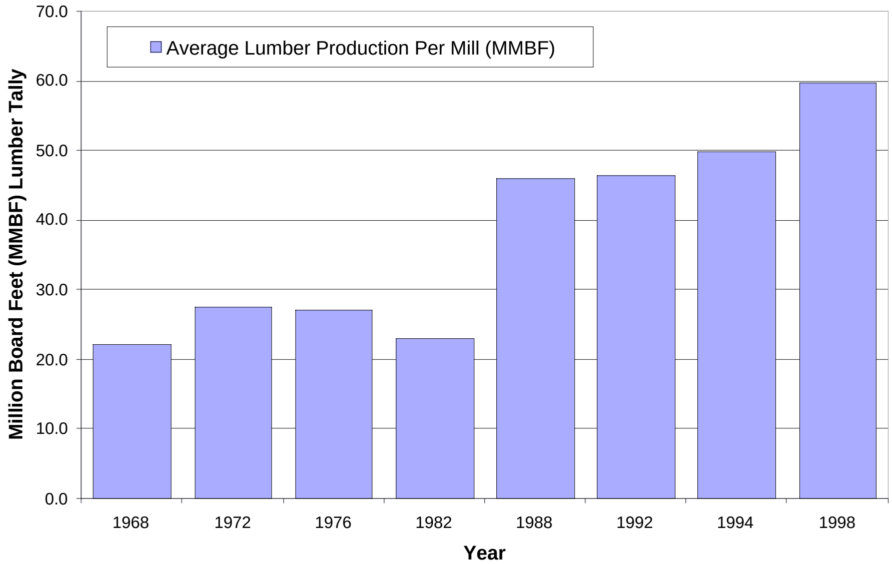
Figure 3: 8-Hour Lumber-Producing Capacity and Lumber Production, 1968-1998



Source: Oregon and Washington mill survey data

Not shown in these figures are changes that occurred over the last three decades in the number and size of mills. In 1968 there were more than 500 sawmills operating in Oregon and Washington.

Figure 4: Average Lumber Production Per Pacific Northwest Sawmill



By 1998, there were less than 170. Accompanying the closure of mills over this time was a strong trend toward larger mills. As Figure 4 shows, the average sawmill in the Pacific Northwest produced approximately 20 MMBF of lumber in1968. By 1998, the average mill production had almost tripled to 60 MMBF.

As Figure 1, Figure 2, and Figure 3 indicate, partial productivity measures, such as labor productivity, would indicate that the Northwest sawmilling industry has experienced productivity growth. However, partial productivity measures do not provide a complete picture of the changing structure of the production function of the sawmilling industry. Rather, total factor productivity (i.e., the ratio of output to *all* inputs) must be examined.

To examine the changing structure of the Northwest sawmilling industry, this project addresses five important questions. 1) How has the average rate of technical efficiency in the Northwest sawmilling industry changed during the 1968 to 2002 time period? 2) Has the sawmilling industry operated at a scale efficient level during this period? 3) What has been the rate of productivity growth during the 1968 to 2002 time period? 4) How have the three components of productivity change (i.e., technical change, efficiency change, and scale efficiency change) impacted productivity growth over this period? 5) Has the substitutability relationship between inputs changed over this period and if so, how?

To answer these questions, data envelopment analysis (DEA) and stochastic frontier analysis (SFA) methods were employed. Neither of these techniques have been previously applied to the Northwest sawmilling sector. The two methods differ from traditional econometric approaches in two fundamental ways: first, as the names imply, DEA and SFA are methods of estimating the frontier or limit of the data. With respect to the production function, DEA and SFA estimate the production frontier (also referred to as the "best practices frontier"). Conversely, traditional econometric approaches estimate the *average* production function. Second, unlike traditional econometric approaches, DEA and SFA do not require assumptions regarding firm behavior, such as cost minimization or profit maximization. In addition to the questions posed above regarding changes in the structure of the Northwest sawmilling industry, this project also provides a comparison of results obtained through DEA and SFA. There is a relatively large and growing body of literature that employs either DEA or SFA methods. However, to the best of our knowledge there are very few analyses that compare results obtained through these two methods.

The project is comprised of three separate but unified analyses.

In Chapter 2, DEA is employed to examine the technical and scale efficiency of the Washington State sawmilling industry. In addition, the industry's rate of productivity growth and technical change are estimated using the Malmquist input-oriented productivity index. Analysis is based on a 3-input, 1-output production process.

In Chapter 3, SFA is employed to examine productivity growth and the components of productivity growth: technical change, efficiency change, and scale efficiency change, in the Oregon and Washington sawmilling industry. In addition, output elasticities and input substitution elasticities are examined for three different time periods. Analysis in Chapter 3 is based on a 4-input, 1-output production process.

In Chapter 4 DEA is employed to examine the technical and scale efficiency of the Oregon and Washington sawmilling industry. The industry's rate of productivity growth and technical change are estimated using the Malmquist output-oriented productivity index. Analysis is based on a 4-input, 1-output production process. Following the methods described by Simar and Wilson (1998, 1999, 2000a, 2000b, 2002), the smoothed bootstrap technique is used to construct confidence intervals for the technical efficiencies and Malmquist productivity indices. The results of this analysis are compared to the results obtained in Chapter 3.

Productivity Growth, Technical Change, and Returns to Scale in the Washington State Sawmill Industry

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Productivity Growth, Technical Efficiency, And Returns To Scale In The Washington State Sawmill Industry

Introduction

Beginning in the mid-to-late 1980s, the timber industry in the U.S. Pacific Northwest began experiencing significant and highly publicized employment declines. Between 1980 and 1990, employment in Washington's sawmill industry declined almost 14%, and between 1990 and 2000 employment declined 20%. Lumber production in Washington State did not decline by a corresponding amount, but instead increased by 27% between 1980 and 1990 and by 11.5% between 1990 and 2000.[2] Given these changes in employment and lumber production, it is clear that the Washington State sawmill industry was making labor-saving changes to its production processes. It is unclear if the changes in employment and lumber production resulted in changes in the overall productivity of the industry.

In this paper we answer two important questions concerning the sawmill industry of Washington State: what was the industry's rate of technical change over the past several decades, and how did technical change impact the industry's productivity growth? We use data envelopment analysis (DEA) to address these two questions by estimating the change in total factor productivity (TFP) that occurred in the sawmill industry of Washington State since the early 1970s.[3] In addition, we use DEA to calculate the rate of

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[2] Lumber production declined in the early 1990s. Reductions in log exports and plywood production, beginning in the mid-1990s, has resulted in a greater proportion of Washington logs being used for lumber production. Production increases have also been attributed to increases in technical efficiency of sawmills. We currently know of no study that tests this hypothesis.

[3] Total factor productivity of a firm is the ratio of the output it produces to *all* inputs it uses. Unlike partial productivity measures, such as labor productivity, TFP provides an overall measure of productivity. Throughout this paper we use productivity and TFP interchangeably.

technical efficiency and scale efficiency of the Washington sawmill industry at the beginning of the 1970s, 1980s, and 1990s, as well as the end of the 1990s.

We begin with an overview of the literature related to the measurement of productivity change in the sawmill industry. We then describe our data and methods before presenting and discussing our empirical results.

LITERATURE REVIEW

Over the past 40 years, many studies have estimated aspects of productivity and technical change in the North American sawmill industry. These studies have generally been performed at a regional level, including the Pacific Northwest and Southeast regions of the U.S. (for examples, see Stevens, 1995; Abt, 1987) and the coastal and inland regions of British Columbia in Canada (for examples, see Constantino and Haley, 1988; Meil and Nautiyal, 1988). Analysis techniques have varied, with many earlier studies attempting to measure productivity and technical change using relatively simple indices and measures of average products (for example, see Ruttan and Callahan, 1962). Later studies employed econometric methods to estimate productivity and technical efficiency indirectly by first estimating profit, production, or cost functions (for examples, see Stevens, 1995; Greber and White, 1982; Merrifield and Haynes, 1985).

Stier and Bengston (1992) reviewed the econometric-based literature on technical change in the forest products industry and found mixed results with the rate of technical change. The authors noted that all of the econometric studies reviewed used a simple time trend as a proxy for technical change. Since there is no theoretical reason to assume that technical change occurs at a constant rate, Stier and Bengston appropriately referred to this practice as a “severe theoretical limitation” of the econometric approach (page 153). None of the analyses reviewed by Stier and Bengston were based on data more recent than 1984.

To the best of our knowledge, the only recent analysis of productivity change in the sawmill industry is Nyrud and Baardsen (2003). The authors used DEA to examine firm-level data of the Norwegian sawmill industry over the period 1974-1991 in order to estimate the technical efficiency of individual producers and the industry's rate of productivity growth. They found that productivity increased on average by 0.82% per year, and that technical change was positive during the entire period and averaged about 0.5% per year.

DATA DESCRIPTION

The lumber production, milling capacity, and log-use data used in this analysis come from the Washington Mill Survey (WMS). The WMS is a biennial survey of sawmills and planning mills (SIC 242), which began in 1968.[4] In order to protect the confidentiality of individual mills, the WMS data were aggregated into regions. The regions represent geographical areas of at least 50% self-reliance with respect to timber supply. The six regions are shown in Figure 5. The Central and Inland Empire regions lie east of the Cascade Mountains. All other regions lie on the westside of the Cascade Range. The Washington Department of Employment Security provided county-level employment data, which were aggregated up to the six regions.

Although the longitudinal aspect of our data set is substantial (17 surveys conducted between 1968 and 2000), each cross-section is comprised of only six observations. In order to increase the discriminatory power of our analysis, we pooled data from consecutive years in the following manner.[5]

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[4] SIC 242 includes SIC 2421 (sawmills and planning mills), SIC 2426 (hardwood dimension and flooring mills), and 2429 (special product sawmills).

[5] The fewer the number of observations in the comparison set, the greater the likelihood that any observation will be projected to lie on the efficient frontier. By pooling the data in the manner described above, we increase the number of observations per cross-section from 6 to 18. DEA results are presented as the geometric mean of each period.

- "Early 1970s" – consisting of data from 1968, 1970, 1972
- "Early 1980s" – consisting of data from 1978, 1980, 1982
- "Early 1990s" – consisting of data from 1988, 1990, 1992
- "Late 1990s" – consisting of data from 1996, 1998, 2000

Table 1 presents descriptive statistics of the output and input variables considered in the analysis. As shown in Table 1, lumber production has increased as mill capacity has increased. Over the three decades, however, both log and labor usage have declined.

METHODS OF ANALYSIS

Farrell (1957) is the seminal work in the empirical literature related to the measurement of technical and productive efficiency. He showed how information on firms' input and output quantities could be represented in a piecewise manner in order to estimate the industry's production frontier. His notion of the production frontier is based on the performance of the industry's most efficient firms rather than theoretical engineering considerations. These ideas were later adapted by Charnes, Coopers, and Rhodes (1978) (CCR) into a linear programming (LP) framework.

CCR advanced Farrell's work in several ways. First, they showed that an analysis of technical efficiency posed as a nonlinear programming problem could be converted into a simple linear programming problem equivalent to Farrell's technical efficiency. They dubbed this approach data envelopment analysis (DEA) and emphasized its general applicability by coining the term decision making units (DMUs). CCR also showed the duality of linear programming-derived technical efficiency measures to other, more common economic functions, such as the cost and Shephard distance function.

Technical Efficiency

To estimate the technical efficiency of each region of Washington State for each period of observation, we employ DEA and estimate Farrell input-oriented technical efficiency. We prefer DEA to traditional regression analysis because we are interested in identifying the best practice rather than an average relationship. Each DMU's performance is compared to the performance of all other DMUs in the industry, thus producing relative measures of technical efficiency. In addition, unlike traditional econometric analyses, the linear programming approach neither requires assumptions regarding firm behavior, such as cost minimization or profit maximization, nor requires imposing a specific functional form for technology, such as Cobb-Douglas, CES, translog, or others.

The best practice frontier or isoquant is constructed from the sample data as illustrated in Figure 6, where all three DMUs (*A*, *B*, and *C*) produce the same amount of output, but with varying amounts of inputs X_1 and X_2. DMUs *A* and *B* are the most technically efficient in their use of the inputs, and, thus, are used to construct the technically efficient frontier and have a Farrell input-oriented technical efficiency measure of unity. DMU *C* is interior to the frontier and has a technical efficiency score computed as the ratio:

$$F_I^C = \frac{(O,D)}{(O,C)} , \tag{4.1}$$

where F_I^C is the Farrell input-oriented measure of technical efficiency for DMU *C*. More formally, the Farrell input-oriented measure of technical efficiency is defined as

$$F_I(y,x) = \min\{\lambda : \lambda x \in L(y)\}, \tag{4.2}$$

where F_I refers to the Farrell input-oriented measure of technical efficiency, (*y, x*) are the vectors of inputs and outputs for the *i*-th DMU, _ is the minimum amount the input bundle can be scaled in order to operate on the efficient frontier, and *L(y)* is the input requirement set, which contains all combinations of inputs that can be used to produce the output vector *y*.

The input requirement set used to construct the efficient frontier is formally constructed as follows:

$$
\begin{aligned}
L(y \mid C,S) = \Big\{ (x_1, x_2, \ldots, x_N) : \\
\sum_{k=1}^{K} z_k y_{km} \geq y_m, m = 1,\ldots, M, \\
\sum_{k=1}^{K} z_k x_{kn} \leq x_n, n = 1,\ldots, N, \\
z_k \geq 0, k = 1,\ldots, K \Big\},
\end{aligned}
\tag{4.3}
$$

where *C* denotes constant returns to scale (CRS), *S* denotes strong disposability of inputs, and z_k are the intensity variables computed by the model. In this formulation CRS is satisfied.

Under the assumption of CRS, a proportional change in all inputs results in a proportional change in output. However, a proportional change in all inputs may not be globally possible. If, for example, one or more inputs are fixed, quasi-fixed, or otherwise restricted, the production process may exhibit decreasing returns to scale (DRS). In such a case, a proportional increase in all inputs will result in a less than proportional change in output—at least along a segment of the production function. Alternatively, if a proportional change in all inputs allows for a more efficient means of production and a greater-than proportional change in output, the production process exhibits increasing returns to scale (IRS) along that segment of the production function. The scale efficiency and returns to scale of a DMU have important economic implications. Namely, a DMU not exhibiting CRS may be either too large or too small.[6]

Under the assumption of CRS, technical inefficiency exhibited by a DMU may be wholly or partially explained by scale efficiency rather than by the inefficient use of inputs. By decomposing technical efficiency measures derived under the assumption of CRS into a pure technical efficiency component and a scale efficiency component, we are able to determine what portion of a DMU's inefficiency is due to the way inputs are used (technical efficiency), and what portion is due to operating in an area of the production function where either IRS or DRS prevails.

In order to measure scale efficiency, an additional LP problem is solved with the constraint that the sum of the intensity variables (the *z*'s) equal unity. This constraint yields a technology allowing for variable returns to scale (VRS). Following the method described by Färe, Grosskopf, and Logan (1983), scale efficiency is defined as the ratio of technical efficiency under CRS to technical efficiency under VRS.

A DMU whose production process exhibits CRS (scale efficiency = 1.0) is said to be scale efficient, whereas a DMU with a scale efficiency less than unity is said to be scale inefficient. To determine if a DMU's scale inefficiency is due to operating at a point of IRS or DRS, an additional DEA model is required. This model is estimated under the assumption of non-increasing returns to scale (NIRS). If a DMU is operating at a point of scale inefficiency (i.e., $S(y, x \mid S) < 1$), then scale inefficiency is due to IRS if $F_i(y, x \mid N, S) = F_i(y, x \mid C, S)$, and due to DRS if $F_i(y, x \mid N, S) > F_i(y, x \mid C, S)$.

[6] It important to note we are examining the behavior of "DMUs in the aggregate," not individual DMUs. Nevertheless, the economic implications regarding scale efficiency are still valid, but certainly difficult or even impossible to ascribe to individual DMUs.

Productivity Growth

Measurements of technical efficiency are the building blocks for measuring TFP (Färe and Grosskopf 1998). Productivity growth is a measure of changes in performance over time, and in the simplest case (single input, single output) it is the change in average product between two periods. In the case of multiple inputs and/or outputs, the distance function is used to aggregate inputs and outputs in order to measure TFP.[7] The input distance function, D_I, is the reciprocal of the Farrell input-oriented technical efficiency measure, F_I.[8] Because of this reciprocal relationship, one can use linear programming to estimate the distance function measures necessary to construct the input-oriented Malmquist productivity index

$$M_I\left(x^{t+k}, y^{t+k}, x^t, y^t\right) = \left[\frac{D_I^t\left(x^{t+k}, y^{t+k} \mid C, S\right)}{D_I^t\left(x^t, y^t \mid C, S\right)} * \frac{D_I^{t+k}\left(x^{t+k}, y^{t+k} \mid C, S\right)}{D_I^{t+k}\left(x^t, y^t \mid C, S\right)}\right]^{1/2}, \tag{4.4}$$

where $D_I^t\left(x^{t+k}, y^{t+k} \mid C, S\right)$ is the input-oriented distance function calculated using technology from time period *t*, input and output quantities from time period *t* + *k*, and assuming constant returns to scale and strong disposability of inputs. $D_I^t\left(x^t, y^t \mid C, S\right)$ is based on technology from time period *t*, and input and output quantities from time period *t*. The remaining distance function components are similarly defined and allow for intertemporal comparisons of productivity.

All of the distance functions are defined relative to CRS technology, which ensures that the Malmquist index can be interpreted as a measure of TFP. As pointed out by Coelli *et al.* (1998), and others, the Malmquist index will not

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[7] For more information on the distance function, quantity indexes, and productivity indexes, see Chambers, Färe, and Grosskopf (1994).

[8] Under the assumption of CRS, the input and output distance functions are reciprocals. Likewise, the input-oriented and output-oriented Farrell technical efficiency measures are reciprocals. The distance function measures used in the development of the Malmquist TFP index can be estimated using either the input-oriented or output-oriented Farrell efficiency measures.

correctly measure TFP change (in the sense of changes in ratios of average products as usually defined) when VRS is assumed for the production process. Therefore, it is important that the distance function estimates used in the calculation of the Malmquist index be computed under the assumption of CRS.

The Malmquist productivity index can be decomposed into various factors affecting productivity change. We employ the decomposition into efficiency change and technical change as in Färe, Grosskopf, Norris and Zhang (1994). Efficiency change is a measure of how well a DMU is adjusting its production function to the existing state of technology. Efficiency change can be thought of as a measure of how well a DMU performed at "catching up" to the state of technology. Efficiency change is computed as:

$$EfficiencyChange = \frac{D_I^{t+k}\left(x^{t+k}, y^{t+k} \mid C,S\right)}{D_I^{t}\left(x^{t}, y^{t} \mid C,S\right)}. \tag{4.5}$$

Again, the distance functions are reciprocals of the Farrell input-oriented technical efficiency measure and are estimated using DEA.

The other component of productivity change is technical change, a measure of shifts in the production frontier. As such, it can be thought of as a measure of how much impact a DMU had in shifting out the efficient frontier of all DMUs. Technical change is computed as:

$$TechnicalChange = \left[\frac{D_I^{t}\left(x^{t+k}, y^{t+k} \mid C,S\right)}{D_I^{t+k}\left(x^{t+k}, y^{t+k} \mid C,S\right)} * \frac{D_I^{t}\left(x^{t}, y^{t} \mid C,S\right)}{D_I^{t+k}\left(x^{t}, y^{t} \mid C,S\right)}\right]^{1/2}. \tag{4.6}$$

As in the calculation of the Malmquist productivity measure, this component of productivity is derived through the calculation of the reciprocals of the distance functions (Farrell technical efficiency) as the solutions to DEA-type linear programming problems. Technical change is the geometric mean of the technology shift between periods t and $t + k$, evaluated at $(x,^t\ y^t)$ and (x^{t+k}, y^{t+k}).

EMPIRICAL RESULTS

We begin by examining the scale efficiency and returns to scale of the sawmill industry by region for each time period (Table 2).[9] For the early 1980s we find that the industry in each region operated at a point of CRS. For the other periods, we find evidence that the industry operated at points of modest scale inefficiency—either at a point of increasing or decreasing returns to scale. The strongest evidence of scale inefficiency is observed for the Central region in the late 1990s (0.76). For the other periods, our findings indicate only modest scale inefficiency and, when averaged across the regions, scale efficiency is consistently above 90%. It should be noted that there are no formal statistical tests for assessing the statistical significance of scale efficiency or returns to scale estimates in DEA models.[10] Therefore, we are unable to conclude with statistical confidence that any of our estimates of scale efficiency differ or do not differ from unity.[11] The fact that our estimates of scale efficiency are (with the one exception noted above) greater than 0.9, indicates that CRS may not be an unreasonable assumption of the industry's technology.

Technical efficiency was estimated under two alternative assumptions. First, we estimated Farrell technical efficiency scores under the assumption of VRS, which results in a measure of technical efficiency that is free of any scale inefficiency. More precisely,

$$F_i(y, x \mid V, S) = F_i(y, x \mid C, S) / S(y, x \mid S). \tag{5.1}$$

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[9] We used GAMS to solve the LPs used to calculate technical and sale efficiency, productivity growth, and technical and efficiency change.

[10] Simar and Wilson (2002) discuss hypothesis testing of returns to scale in DEA. The authors also propose a bootstrap technique, which they claim yields appropriate critical values for the test statistics.

[11] In other words, we are unable to test the null hypothesis that $S_{it} = 1$, where S_{it} is the scale efficiency of sawmill region i evaluated in time period t.

These results are presented in Table 3. Farrell input-oriented technical efficiency scores were also estimated under the assumption of CRS, and represent an overall measure of a DMU's technical efficiency. [12] Table 4 presents these scores.

Based on the assumption of VRS (Table 3), the sawmill industry in each region appears to be operating at near technical efficiency. However, as the results in Table 4 show, when scale efficiency (or rather inefficiency) is part of the measure of technical efficiency (i.e., under the assumption of CRS), only the South Sound, Southwest, and Inland Empire regions are operating at more than 90% technical efficiency. More telling, based on the assumption of VRS, the Central region's estimate of technical efficiency is 0.99 for the late 1990s. Under the assumption of CRS, this drops to 0.75 because of scale inefficiency.

Our results to this point represent only static measures of technology. However, the production function of Washington sawmills has shifted over time as new technologies have become available. Using the Malmquist productivity index, we found that between the early 1970s and early 1980s productivity actually declined in Washington by 0.25% on an average annual basis, as both technical change and efficiency change experienced modest declines (see Table 5, Table 6, and Table 7).

For the rest of the study period we found dramatically different results. Between the early 1980s and early 1990s, productivity increased by 2.1% on an average annual basis, while technical change increased by 1.9% and efficiency experienced modest increases. Although slowing a bit in the ensuing decade, between the early 1990s and late 1990s productivity increased by 1.2% per year and technical change increased by 1.8%. The difference between these two growth rates is explained by negative efficiency change (-0.53%)

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[12] What we refer to as *overall* efficiency does not include allocative efficiency, which is concerned with choosing the minimum cost bundle of inputs to produce a given level of output.

over the period.[13] As positive technical change continued to push out the industry's production frontier, many individual producers were unable to increase their own technical efficiency at the same rate as the industry leaders. Thus, though the industry was more productive at the end of the 1990s than it was at the beginning of the decade, the distance of the average DMU from the efficient frontier actually increased. When considering the entire period, the early 1970s through late 1990s, technical efficiency increased at 1.1% per year, and productivity increased at just less than 1.0% per year.

At the aggregate level, producers in each of the six regions experienced productivity growth over the three-decade study period. However, the rate of productivity growth differed greatly between regions. At an average annual rate of 0.16%, producers in the Central region experienced the lowest rate of productivity growth. At the other extreme, producers in the Coast region experienced average annual productivity growth of 1.77%.

Our results are consistent with Nyrud and Baardsen (2003), who found that productivity growth in the Norwegian sawmill industry averaged 0.82% per year between 1974 and 1991. Though not perfectly overlapping our time periods, Nyrud and Baardsen found that productivity was negative between 1974 and 1982, declining by 2.0% per year on average, and was strongly positive between 1982 and 1991, increasing on an average annual basis of 3.14% per year.

The econometric studies of the Pacific Northwest and Canadian sawmill industry discussed at the beginning of this paper were based on data that, at most, overlap only the first half of our study period. Therefore, comparisons of results are limited to only these earlier years. Constantino and Haley (1988)

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[13] Under the assumption of CRS, the efficiency change component of the Malmquist productivity index is actually composed of technical efficiency change and scale efficiency change. See Färe *et al*. (1994) for a discussion on the decomposition of efficiency change into these two components.

found that over the period 1957-1981, technical change averaged 0.6% per year for the British Columbia coast and the U.S. Pacific Northwest. Unfortunately, the authors did not provide technical change estimates for just the last decade of their analysis, so truly meaningful comparison is not possible. Abt (1987) did not provide estimates of productivity or technical change, but found that the industry operated under CRS between 1963 and 1978. Merrifield and Haynes (1985) concluded that over the period 1950-1979, technical change was "slight." Meil and Nautiyal (1988) found no significant increases in productivity between 1968 and 1984 for the British Columbia coast or interior. Stevens (1995) reported "neutral" technical change occurred in western Washington between 1980 and 1988, but the author did not report the rate of technical change.

According to Stevens (1991), the sawmill industry made little investment in machinery and equipment between 1980 and 1988, and little technical change occurred over the period. Stevens' findings appear to be contrary to the results of our study, which found strong technical change between the early 1980s and early 1990s. The discrepancy in findings may be due to the slight difference in time periods considered. Alternatively, it may be due to the fact that Stevens (1991), like other econometric approaches, attempts to measure technical change through a time proxy, whereas DEA allows for the direct measurement of technical change.

DISCUSSION

The results of this study provide quantitative answers to two fundamental questions concerning the sawmill industry of Washington State over the past few decades. Namely, what has been the rate of technical change in the industry and how has it impacted productivity growth? We found that while the industry experienced slightly declining productivity in the 1970s, it experienced rapid growth in productivity during the 1980s and 1990s.

Decomposing productivity growth into efficiency change and technical change, we found that it was technical change that was responsible for the rapid growth in productivity over this period. However, our analysis does not shed light on why productivity and technical change were flat during the 1970s but were strong during the subsequent periods.

The decline in the size and quality of logs that occurred over the study period is widely believed to have increased sawmill productivity. Although less valuable, the processing of smaller logs is less labor intensive and more amenable to mechanization. Lower quality logs also lend themselves to mechanization as they are unsuitable for higher valued processing, which is generally more labor intensive. The 1980s also saw a decline in union representation of sawmill workers, leading to the relaxation of rigid work rules and perhaps to greater productivity (Stevens, 1991).

This study is the first in many years to examine productivity growth in the Washington State sawmill industry. To our knowledge, it is also the only study to examine any portion of the Pacific Northwest sawmill industry using DEA. Given the strong growth in productivity that we found for the 1980s and 1990s, it is surprising that greater attention has not been paid to this important regional industry.

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Table 1: Descriptive Statistics for Lumber (output) and Logs, Labor, Capital (inputs), 18 DMUs per Time Period

Variable	Stat	Early 1970s (1970-1972)	Early 1980s (1980-1982)	Early 1990s (1990-1992)	Late 1990s (1996-2000)
Lumber – Output (MBF, lumber tally) average annual production	Mean	598,100	570,494	691,316	727,729
	SD	206,927	214,344	277,256	318,253
	Min	316,760	234,160	359,187	302,888
	Max	960,780	1,060,200	1,190,400	1,245,573
Logs (MBF, net scale) average annual consumption	Mean	479,141	424,798	454,645	408,536
	SD	167,607	147,345	173,898	160,094
	Min	257,870	168,270	223,315	201,249
	Max	731,340	768,590	834,660	711,020
Labor (SIC 242) average annual employment	Mean	3,008	3,186	2,681	2,268
	SD	1,079	1,413	1,334	1,393
	Min	1,334	1,355	1,397	1,041
	Max	5,045	5,884	5,543	5,135
Capital (max capacity per 8-hour shift, MBF, lumber tally)	Mean	1,798	1,975	2,065	2,139
	SD	576	605	749	952
	Min	1,082	980	1,063	883
	Max	2,721	2,933	3,036	3,944

Note: "MBF" is read as "thousand board feet." A board foot, the traditional unit of measure of log volumes in the Pacific Northwest, is a 12-inch square piece of wood that is 1-inch thick. Log scale is a centuries-old measurement used to approximate the number of board feet of lumber that can be produced from a log. Lumber tally is a measure of the actual amount of lumber produced.

Table 2: Scale Efficiency Estimates and Returns to Scale

Region	Early 1970s (1970-1972)	Early 1980s (1980-1982)	Early 1990s (1990-1992)	Late 1990s (1996-2000)
North Sound	0.97 – DRS	1.00 – CRS	0.99 – DRS	0.99 – DRS
South Sound	1.00 – CRS	1.00 – CRS	1.00 – CRS	0.99 – DRS
Coast	0.91 – IRS	1.00 – CRS	0.94 – DRS	0.96 – DRS
Southwest	0.99 – DRS	1.00 – CRS	1.00 – CRS	0.90 – DRS
Central	0.99 – IRS	1.00 – CRS	0.92 – DRS	0.76 – DRS
Inland Empire	0.91 – IRS	1.00 – CRS	0.99 – DRS	0.94 – DRS
Washington	0.96 – DRS	1.00 – CRS	0.97 – DRS	0.92 – DRS

Table 3: Input-Oriented Farrell Technical Efficiency Scores Under VRS

Region	Early 1970s (1970-1972)	Early 1980s (1980-1982)	Early 1990s (1990-1992)	Late 1990s (1996-2000)
North Sound	0.92	0.86	0.88	0.88
South Sound	1.00	0.98	0.98	0.97
Coast	1.00	0.81	0.95	0.99
Southwest	0.91	0.97	0.99	1.00
Central	0.93	0.95	0.94	0.99
Inland Empire	1.00	0.90	0.98	0.98
Washington	0.96	0.91	0.95	0.96

Table 4: Input-Oriented Farrell Technical Efficiency Scores Under CRS

Region	Early 1970s (1970-1972)	Early 1980s (1980-1982)	Early 1990s (1990-1992)	Late 1990s (1996-2000)
North Sound	0.90	0.86	0.87	0.87
South Sound	1.00	0.98	0.98	0.96
Coast	0.91	0.81	0.89	0.95
Southwest	0.90	0.97	0.99	0.90
Central	0.92	0.95	0.86	0.75
Inland Empire	0.91	0.90	0.97	0.92
Washington	0.92	0.91	0.93	0.89

Table 5: Malmquist Productivity Growth, Average Annual Growth Rates

Region	Early 1970s to Early 1980s	Early 1980s to Early 1990s	Early 1990s to Late 1900s	Early 1970s to Late 1990s
North Sound	-0.60%	1.34%	2.12%	0.74%
South Sound	0.26%	2.54%	1.69%	1.11%
Coast	-0.98%	2.30%	3.31%	1.77%
Southwest	0.79%	3.41%	-0.01%	1.16%
Central	-0.58%	0.25%	0.07%	0.16%
Inland Empire	-0.39%	3.00%	0.26%	0.91%
Washington	-0.25%	2.13%	1.23%	0.98%

Table 6: Technical Change, Average Annual Growth Rates

Region	Early 1970s to Early 1980s	Early 1980s to Early 1990s	Early 1990s to Late 1900s	Early 1970s to Late 1990s
North Sound	-0.07%	1.17%	2.13%	0.86%
South Sound	0.46%	2.50%	2.05%	1.27%
Coast	0.12%	1.32%	2.53%	1.60%
Southwest	0.10%	3.07%	1.31%	1.20%
Central	-0.87%	1.29%	1.65%	0.89%
Inland Empire	-0.21%	2.14%	0.93%	0.86%
Washington	-0.08%	1.91%	1.76%	1.11%

Table 7: Efficiency Change, Average Annual Growth Rates

Region	Early 1970s to Early 1980s	Early 1980s to Early 1990s	Early 1990s to Late 1900s	Early 1970s to Late 1990s
North Sound	-0.47%	0.17%	-0.01%	-0.12%
South Sound	-0.20%	0.06%	-0.34%	-0.16%
Coast	-1.07%	0.98%	0.76%	0.16%
Southwest	0.65%	0.33%	-1.32%	-0.03%
Central	0.28%	-1.06%	-1.55%	-0.71%
Inland Empire	-0.12%	0.79%	-0.68%	0.04%
Washington	-0.16%	0.21%	-0.53%	-0.14%

Figure 5: Washington State Sawmill Regions

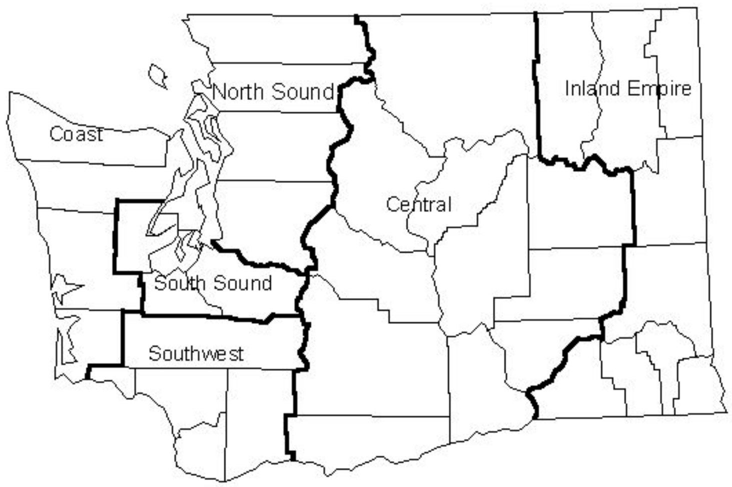
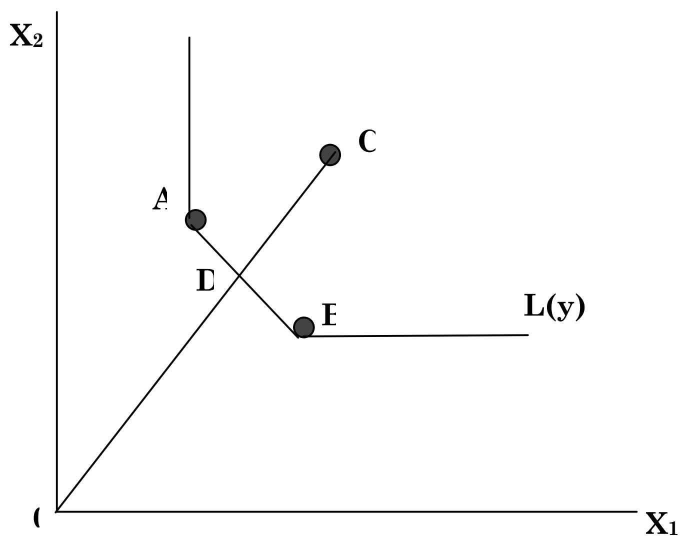


Figure 6: Best Practices Frontier in Input Space



Productivity Growth, Technical Change, and Time-Varying Elasticity of Substitution in the Northwest Sawmill Industry: A Stochastic Frontier Approach

Ted L. Helvoigt

PRODUCTIVITY GROWTH, TECHNICAL CHANGE, AND TIME-VARYING ELASTICITY OF SUBSTITUTION IN THE NORTHWEST SAWMILL INDUSTRY: A STOCHASTIC FRONTIER APPROACH

INTRODUCTION

Beginning in the late 1980s and continuing into the 21st century, the sawmill industries of Oregon and Washington ("the Northwest") experienced substantial employment declines. Beginning even earlier and continuing into the new century, the northwest sawmill industry is believed to have experienced substantial technical change, which resulted in productivity growth. Much of the speculation regarding technical change and productivity growth in the industry has been anecdotal and, to the best of the author's knowledge, has not been empirically validated. In this paper estimates of technical change, efficiency change, and productivity growth are developed for the Northwest sawmill industry. In addition, output elasticities, scale efficiency, and Morishima elasticities of substitution between input factors are estimated. These economic measures are developed based on the formulation and estimation of a stochastic frontier production function (SFPF) model, a method of analysis which has not been previously applied to the Northwest sawmill sector. The analysis uses a unique panel of mill-level data, as well as data from published reports of regionally-aggregated information of mill characteristics and activity.

Although its relative shares of the Oregon and Washington economies have slowly declined over the past decades, the forest products industry in the Northwest continues to be a major source of employment and economic output. Because of its historic and continued importance to the economy and culture of the Northwest and its particular importance to individual communities in the Northwest, it is important to understand how the structure of the forest products industry has changed. The results of this analysis provide such valuable insights.

This analysis departs from past analyses of the Northwest sawmill industry and from analyses of the sawmill industry in other North American regions. First, the SFPF allows for the direct estimation of technical efficiency, as well as the estimation of technical change through time. Second, earlier studies assumed lumber producers to be successful cost minimizers or profit maximizers, and thus employed OLS or other regression techniques to estimate cost, profit, or production functions. Implicit within these approaches is the assumption that any deviation from minimum cost or maximum profit is simply random noise. In contrast, the SFPF approach both estimates the frontier of the industry production function and measures the technical efficiency of individual producers (or aggregates of producers) relative to the frontier. The SFPF does not require the assumption that producers are acting in an economically optimal fashion. Third, this study pays closer attention to regularity conditions than previous studies.

The two principal methods of frontier estimation are stochastic frontier analysis (SFA) and data envelopment analysis (DEA).[14] Although the two methods differ in many ways, the primary difference is that SFA relies on econometric-based estimation methods, whereas DEA relies on mathematical programming. Both of these approaches were alluded to, but not actually estimated, in Farrell's (1957) seminal work.[15] The two methods estimate the industry's technical frontier based on the performance of the most technically efficient (i.e., most productive) decision making units (DMUs). Measures of the technical efficiency of each DMU are then estimated based on the distance of the DMU from the technical frontier. Estimates of productivity and/or

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[14] The *stochastic frontier production function* is one model within the *stochastic frontier analysis* method.

[15] Farrell (1957) suggested that technical efficiency could be estimated by either piecewise linear programming or a parametric function.

technical efficiency derived from SFA and DEA methods are relative measures, not absolute measures.

Stochastic Frontier Analysis of the Forest Products Industry

There are few studies of the wood products industry that employ stochastic frontier analysis and none conducted specifically for the sawmill industry. Carter and Cubbage (1995) estimate a stochastic frontier production function using firm-level data from the southern U.S. pulpwood harvesting industry for 1979 and 1987. However, the data do not include a firm identifier, and so there is no means of linking a firm's production in 1979 with its production in 1987. The data set consists of two cross-sections, but it is not a panel.

The authors estimate four stochastic production frontier models, one each based on the 1979 and 1987 data, and two models based on combining the two years of data. Included in the two combined models is a dummy variable for time. The authors find the industry's average level of technical efficiency to be 60% in both 1979 and 1987, and that the industry experienced positive technical change that averaged 1.8% per year over the eight-year period. In the second stage of the analysis, the authors use OLS to regress the estimated technical efficiency measures (from the "first stage") on characteristics of the pulpwood producers. The purpose of this second stage model is to explain the sources of technical inefficiency. Variables on the RHS of the OLS regression model include owner age, years of experience, and number of employees. The second stage model was able to explain approximately 20% of the variation in the technical efficiency measures.

This analysis has two important limitations. First, the authors consider a production function of average weekly pulpwood production using only two inputs, labor (the number of employees plus the owner) and capital (the replacement value of the assets). Other inputs, such as energy, supplies, and most importantly stumpage, were not considered because there were no data. Second, the specification and estimation of the stochastic production function is done under the assumption that the technical inefficiency effects are identically distributed.[16] The second stage model requires the specification of a regression model for the predicted technical inefficiency measures, thus contradicting the assumption of identically distributed inefficiency effects in the stochastic production frontier model.

Siry and Newman (2001) study the efficiency of Polish state timber production and management policies for the years 1993-1995, a period of rapid change in Polish forestry. In 1989, timber prices were released from state control and the Forest Act of 1991 was intended to help speed the transition of the state-controlled forests to more market-based management. The authors examined data for 40 forest districts over the three year-period. The measure of output was volume of timber sales, and inputs included forestland area, growing stock volume, permanent and temporary forest workers, administrative employees, kilometers of roads, personnel vehicles, logging trucks and tractors, and, as a measure of privatization, the share of external costs to total operating costs. A time-invariant Cobb-Douglas production function was used to represent technology.

The authors note that the use of the Cobb-Douglas function is potentially problematic because it is inflexible and restrictive. A translog model was specified and estimated, but failed due to the large number of coefficients (50) and relatively small number of observations (120). The time-invariant specification was tested against a time-varying specification using a likelihood ratio test. The null hypothesis of time-invariant technical change could not be rejected. It may be that the time span of the panel (only three years) was too short to observe changes in technical efficiency. All estimated elasticities had the expected positive sign, except administrative employees, which was negative and statistically significant. Because of this negative elasticity, the estimated production function violates the properties of monotonicity and

[16] For more information on the assumptions of the one-sided (inefficiency effects) error term, see Battese and Coelli (1995).

quasiconcavity, "casting some doubt on the validity of the function" (Siry and Newman, 2001 p530). Nevertheless, the authors believe that this result may be consistent with management practices during this period, which included incentives to maintain and even add administrative personnel.

The mean technical efficiency of the 40 forest districts over the three years of analysis is 0.49, and the individual technical efficiencies range between 0.25 and 0.88, indicating that many of the forest districts could vastly improve their efficiency. The authors do not examine technical change or productivity change over the three-year study period.[17] Technical change could have been estimated through the derivative method had the authors included time in the production function (see Kumbhakar and Lovell, 2000 pp284-287), or through the ratio of distance functions derived from the technical inefficiencies estimates (see Coelli, Raw, O'Donnell, and Battese 2005 chap 11).

Yin (2000) analyzes the productive efficiency of global producers of bleached softwood kraft pulp (BSKP). The author employs SFA, estimating both a translog stochastic production frontier and translog stochastic cost frontier on a 1996 cross-section of 102 producers.[18] The author finds that the estimated technical efficiency of every producer was above 0.99, indicating essentially no variation in relative technical efficiency. He surmises that the lack of variation could be due to the nature of the production process, the data generating process, and the SFA method. He concludes that DEA "could be a better approach in the current context" and that "different methods [of analysis] can cause variations in empirical outcomes."

[17] In fact, the authors do not include time in the production function.

[18] The author also analyzes the efficiency of the BSKP producers using DEA.

THE THEORETICAL MODEL

The stochastic frontier production function was developed independently by Aigner, Lovell, and Schmidt (1977), and Meeusen and van Den Broeck (1977). The approaches presented in the two papers are substantively the same, but differ with respect to the distributional assumptions of the error term. The two papers share the same convention of assuming an error term that is composed of two random variables, v_i and u_i. The first component, v_i, is a random variable that accounts for measurement error and other random factors, and it can be positive or negative. The second component, u_i, is a non-negative random variable that measures the deviation from the efficient frontier of the i-th observation. Since 1977, researchers have introduced modifications and innovations to the stochastic frontier model. However, the basic structure of the model remains unchanged. Stochastic frontier analysis models the *frontier* production (or cost) function, rather than the *average* function estimated in a least squares-based analysis. The stochastic production function is defined by

$$y_i = x_i\beta + v_i + u_i \, . \qquad (1)$$

Where y_i is the natural logarithm of output for the i^{th} decision making unit (DMU)[19] and (i = 1,…, N), x_i is a (1 _ k) vector of the natural logarithm of input quantities used by the i^{th} DMU, and β is an (k _ 1) vector of coefficients to be estimated. The components of the disturbance term, v_i and u_i, are assumed to be independent. The model is called a stochastic frontier production function because the output values are bounded from above by the stochastic variable $e^{(x_i\beta+u)}$ (Coelli *et al*. 1998 p185).

[19] The term DMU was introduced by Charnes, Cooper, and Rhodes (1978) and refers to any level of decision maker, e.g. an individual, a group of individuals, a firm or group of firms, or a government agency.

Battese and Coelli (1995) show that the (cross-sectional) stochastic frontier production function presented in equation 1 can also be specified for panel data as

$$y_{it} = x_{it}\beta + v_{it} + u_{it} \,, \tag{2}$$

where y_{it} is the natural logarithm of output for the i_{th} DMU (i = 1,…, N) in the t_{th} time period (t = 1,…, T), x_{it} is a (1 _ k) vector of the natural logarithm of input quantities used by the i^{th} DMU in the t^{th} time period, v_{it} and u_{it} *are the components of the disturbance term,* and β is a (k _ 1) vector of coefficients to be estimated.

Kumbhakar, Ghosh, and McGuckin (1991), and Reifschneider and Stevenson (1991) proposed models for cross-sectional data that simultaneously estimate the stochastic production function and an explicit model of the inefficiency effects associated with the stochastic production function. Battese and Coelli (1995) extended these ideas to panel data models, allowing for both the estimation of technical change (in the stochastic production function) and the estimation of time-varying inefficiency effects (Battese and Coelli 1995). The inefficiency effects specification for the panel data model is as follows:

$$u_{it} = z_{it}\delta + w_{it} \,, \tag{3}$$

where u_{it} is the estimated one-sided inefficiency for the i^{th} DMU in time period t, z_{it} is a vector of characteristics intended to explain the inefficiency of the i^{th} DMU in time period t, δ is a vector of coefficients estimated in the inefficiency model, and w_{it} is defined by the truncation of the normal distribution with zero mean and variance σ^2.[20]

[20] Battese and Coelli (1995) state "the W-random variables are not identically distributed nor are they required to be non-negative…"

The stochastic production function and inefficiency effects model are estimated simultaneously using maximum likelihood methods. The estimates of technical efficiency for i^{th} DMU in time period t is given by

$$TE_{it} = e^{-U_{it}} = e^{-z_{it}\delta - w_{it}} . \quad (4)$$

The stochastic frontier production function has several advantages over DEA. First and foremost, because SFA is an econometric-based method, it allows for the estimation of standard errors and, hence, hypothesis testing using standard maximum likelihood techniques. As the name indicates, the estimated frontier allows for random noise within the data, thus not all deviations from the efficient frontier are attributed to technical inefficiency. SFA also supports panel data estimation, whereas with DEA, a new production possibilities frontier must be established for each year of data.

The stochastic frontier production function is not without shortcomings. Perhaps the most often cited criticism of this model is that there is not an *a priori* theoretical reason to choose one distributional assumption for the u_i over another. Typically, the error term is assumed to be distributed *normal–half-normal* or *normal–exponential*, both of which are single-parameter distributions.[21] Green (1997) found little difference in the parameter estimates and the estimated u_is between models estimated with either of these distributions. Green (1990) proposed a more general two-parameter gamma distribution, but as he later states in Green (2002), "the gamma model brings with it a large increase in the difficulty of computation and estimation." Another criticism of more practical importance is the choice of functional form for technology. There are numerous choices varying from the restrictive, such as the Cobb Douglas or CES, to the flexible, such as the

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[21] Actually, these distributions contain two distribution parameters, σ_v and σ_u, where σ_v is the variance of the normally distributed random error term and σ_u is the variance of the half-normal or exponentially distributed (non-negative) random variable that measures deviations from the efficient frontier. It is the distribution of this portion of the error term that is of interest here.

translog. Theory often provides little guidance in the choice of functional form, and this lack of guidance may explain why the majority of published studies that estimate the SFPF use the flexible translog functional form.

There are advantages to panel data (relative to cross-sectional data) when estimating SFA models. Because a panel data set contains multiple observations on each DMU, it contains information not available from adding DMUs to a cross-section. As the time dimension of the panel data gets larger, the consistency of the technical efficiency estimates of each DMU is increased (Kumbhakar and Lovell, 2000 p96). In the cross-sectional SFA model, it is assumed that the u_i s are distributed independently of the regressors and each other. This is likely an unrealistic assumption for many industries. In the panel data-based SFA model, the independence assumption is relaxed and the additional observations on each DMU provide additional information with which to estimate technical inefficiency for the DMU. Perhaps most important in the context of SFA, panel data allows for the simultaneous examination of technical change and changes in technical efficiency over time (Coelli, Prasada Rao, Battese, 1998 p202). Kumbhakar and Lovell (2000 p285) shows how the components of productivity change can be estimated within the SFPF framework.

THE DATA

This analysis assumes that the production of lumber is a function of four inputs: sawlogs, labor, capital, and *other inputs*. The variables are discussed in greater detail below and descriptive statistics are presented in Table 8. Data were collected from Oregon and Washington mill studies. Mill-level data on lumber production, sawlog consumption, and milling capacity were obtained for Washington sawmills from The Washington Department of Natural Resources (WDNR). The WDNR collects these data through its biennial mill survey. Data for 1968 through 2002 (a total of 18 time points) are used in this analysis. In order to protect the confidentiality of the individual mills, the mill-level data were aggregated into regions. Several regional designations were considered. For western Washington, the regional breakout presented in Adams *et al.* 1992, as well as breakouts resulting in a greater number of smaller regions were considered. Because of the relatively large number of lumber producers on the westside, it was theoretically possible to create a large number of regions while still maintaining mill-level confidentiality. However, problems arose when trying to merge mill-level data aggregated to the county level with county-level data on sawmill employment.[22] In Washington as well as other states, employers are required to report on a quarterly basis the hours and earnings of all employees covered by workers compensation insurance (i.e., unemployment insurance). However, employers are not required to report the hours and earnings of an employee from the actual physical location that the work occurred, although it is common for many companies to do so.[23] A company with two or more mills in a state may report the hours and earnings of all employees as associated with just one of the mill locations, even when the two mills are not within the same county. Thus, county-level employment data do not necessarily coincide with the number of employees who actually worked in the county.

Employment data were available at the county or multi-county level that matched each of the regional designations considered for the westside of Washington. However, by calculating simple labor productivity measures (lumber production divided by employment), it became apparent that county-level employment in SIC 242 in western Washington, as reported by the Washington Employment Security Department, did not correspond well with county-level lumber production levels. It was also not possible to reallocate the county-level employment data to the counties in which the work was actually performed.

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[22] Employment data were not collected in the mill surveys, and therefore employees per mill is not known. The mill surveys collected information on hours per shift, number of shifts per day, and number of operating days per year.

[23] As unemployment insurance programs are operated at the state-level, hours and earnings information must be reported within the state in which the work occurred, but not within the actual county.

To alleviate the disparity between the county-level employment data and the mill-level production data, only two regions were designated for western Washington. All westside counties known to contain one or more mills owned by certain large lumber producers were placed in one region (Region 2) and all other westside counties were placed in the other (Region 1) (see Figure 7).[24] The employment reporting problems observed for western Washington either did not exist or were not particularly severe in eastern Washington. Although producing substantially less lumber than western Washington (especially in recent years), eastern Washington was segmented into three regions: north central (Region 3), south central (Region 4), and the Inland Empire (Region 5) (see Figure 7).

Mill surveys similar to those for Washington State were also conducted for Oregon sawmills, however mill-level data are not available, and mill surveys were not conducted as often as they were in Washington. Survey data were obtained for Oregon for the years 1972, 1976, 1982, 1985, 1988, 1992, 1994, and 1998. Data from the surveys were published at the county or multi-county level by the Pacific Northwest Forest and Range Experimental Station.[25] From these data, four regions were configured (Regions 6 through 9) (see Figure 7). The Oregon mill surveys provide information on the lumber-producing capacity, the volume of sawlogs processed, and the amount of lumber produced per county/county group. Data on SIC 242 employment by county/county group were obtained from the Oregon Employment Department for all relevant years.

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[24] Consolidating the counties this way ensured that the employment and lumber production of western Washington's larger lumber producers were aggregated correctly. A simple calculation of labor productivity (output/employment) for each of the two western Washington regions over the 18 year of observation appeared reasonable and trended in a similar manner.

[25] Because the number of sawmills in Oregon decreased substantially between 1970 and 1998, county groups have become consistently larger and fewer.

Output and Input Variables

Lumber is the total volume in million board feet (MMBF) lumber tally of hardwood and softwood lumber produced by the mills of each region.

Capital is measured as the total installed lumber producing capacity in thousand board feet (MBF) per 8-hour work shift.

Labor is the total man hours worked by each region's SIC 242 employees during the year. Labor is calculated as *Labor = Total SIC 242 Employment * Average Operating Days*[26] ** Average Number of Eight-hour Work Shifts*[27] ** 8 Hours*.

Sawlogs is the total volume in MMBF log scale of hardwood and softwood sawlogs utilized by the region's mills.[28]

Other Inputs is an estimate of the quantity of energy and operations and maintenance supplies used in the manufacture of lumber deflated to 1970 dollars. These costs were not measured in either the Washington or Oregon mill surveys and could not be directly obtained from other sources. Rather, the costs were approximated for each region by developing indices of the average quantity of energy and supplies used in the manufacture of lumber.[29] The

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[26] Average Operating Days is calculated from mill-level data and was weighted based on each mill's lumber production.

[27] Average Number of Eight-hour Shifts is also calculated from mill-level data and was weighted based on each mill's lumber production.

[28] For westside mills, log volumes are measured on a 32-foot Scribner basis, whereas eastside mills measure logs based on a 16-foot Scribner basis. The reason for the difference is due the typical log lengths produced from westside and eastside forests. It is assumed in this analysis that the different scaling bases are incorporated into the production function of each mill and are a function of estimated lumber recovery.

[29] Separate indices were developed for Oregon's and Washington's westside and eastside mills (four indexes in total), based on historical input cost data published by Resource Information Systems, Inc. (RISI). The indices were created by deflating the current year cost of energy and supplies required to produce one MBF of lumber. Energy costs were deflated based on *Industrial Sector Energy Prices* obtained from the Energy Information Administration. Operation and maintenance supply costs were deflated by the Producer Price Index for *Intermediate Materials: Supplies and Components*.

indices were multiplied by the lumber output of each DMU in each year, resulting in a quantity-like measure of energy and operation and maintenance supplies usage ("other inputs").

EMPIRICAL MODEL

In this study, the translog functional form is used to represent the state of technology:

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{4} \beta_k \ln x_{kit} + \beta_t t + \frac{1}{2} \sum_{k \le j}^{3} \sum_{j=1}^{3} \beta_{kj} \ln x_{kit} \ln x_{jit} + \frac{1}{2} \beta_{tt} t^2 + \sum_{k=1}^{4} \beta_{kt} t \ln x_{kit} + v_{it} - u_{it} \, , \quad (5)$$

where

y_{it} represents the quantity of lumber output of the ith DMU in time period t;

x_{1it} represents the milling capacity per 8-hour shift of the ith DMU in time period t;

x_{2it} represents the total man hours utilized by the ith DMU in time period t;

x_{3it} represents the quantity of sawlogs consumed by the ith DMU in time period t;

x_{4it} represents the quantity of the input "other" utilized by the ith DMU in time period t;[30]

t represents the year of observation (1968 = 1)

v_{it} and u_{it} are, respectively, the symmetric and one-sided random error terms defined above.

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[30] By construction, "other inputs" is strongly correlated with the dependent variable. Because of this, the production relationship was simplified by not including the cross-product or squared terms for "other." A likelihood ratio test was conducted to test the null hypothesis that the sum of the coefficients was indeed zero. The results of the likelihood ratio test are presented in the Empirical Results section.

The inefficiency effects model is specified as:

$$u_{it} = \delta_0 + \delta_1 * Time + \delta_3 * Oregon\ , \tag{6}$$

where *Time* represents the year of observation (1968 = 1), and *Oregon* is a dummy variable that equals 1 for regions located in Oregon. The dummy variable for Oregon regions was included to account for possible differences in mill survey development and data collection, as well as differences in species composition of logs delivered to the respective mills.

The purpose of the inefficiency effects model is to explain differences in the estimated inefficiencies of the DMUs. A primary reason for conducting frontier-based estimation is to obtain estimates of inefficiency and to explain variation in inefficiency across DMUs and through time. Because of the assumption that the inefficiency effects are identically distributed, estimation of an inefficiency effects model must occur simultaneously with the estimation of the underlying production function, as opposed to through a second-stage model.[31]

Based on the specification of equation 6, it is assumed that a major source of heterogeneity between the lumber-producing regions is due to inefficiency differences between producers in the two states.

Measuring Productivity Change

Productivity change occurs when the rate of change in output differs from the rate of change in the use of an index of inputs (Kumbhakar and Lovell, 2000 p279). Total factor productivity (TFP) can be measured using either mathematical programming techniques or econometric methods to construct the Malmquist productivity index. The Malmquist productivity index neither requires price information for a firm, nor requires the traditional economic

[31] See Battese and Coelli (1995) for further explanation.

behavior assumptions of cost minimization or profit maximization. Rather, it requires only a representation of the production technology, such as the translog production function. The Malmquist productivity index is a measure of TFP of a DMU based on the ratio of total output quantity to an index of all input quantities. Unlike partial productivity measures, such as labor productivity, TFP provides an overall measure of productivity. Throughout this paper, productivity and TFP are used interchangeably.

Productivity change is the sum of three components: technical change, efficiency change, and scale efficiency, each of which can be derived from coefficients estimated in the SFPF.[32] Assuming the time-varying production function expressed in equation 1, the three components of productivity change are developed as follows (Kumbhakar and Lovell, 2000 p284-286; Coelli, Rao, O'Donnell, and Battese, 2005 p301):

Technical Change: $\hat{T}\Delta = \hat{\beta}_t + \hat{\beta}_{tt}t + \sum_k \hat{\beta}_{kt} \ln x_{kit}$, (7)

Efficiency Change: $TE\Delta = e^{-u_{it}} / e^{-u_{is}}$, (8)

where $e^{-u_{it}}$ and $e^{-u_{is}}$ are the estimated technical efficiencies of the i-th DMU in time periods t and s $(t > s)$ *and* $e^{-u_{it}}$ and $e^{-u_{is}}$ are bounded by zero and unity.

Scale Efficiency: $(\hat{\varepsilon} - 1) \cdot \sum_n \left(\frac{\hat{\varepsilon}_n}{\hat{\varepsilon}} \right) x_n$. (9)

Where $\hat{\varepsilon}_n = \hat{\beta}_n + \sum_k \hat{\beta}_{nk} \ln x_{kit} + \hat{\beta}_{nt}t$ is the output elasticity of input n, and k represents the index of other inputs (k = 1,2,3,4).

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[32] If price information were available, productivity change could be further decomposed into a fourth component, allocative efficiency, which is concerned with choosing the minimum cost bundle of inputs to produce a given level of output.

$\hat{\varepsilon} = \sum_n \left(\hat{\beta} n + \sum_k \hat{\beta}_{nk} \ln x_{kit} + \hat{\beta}_{nt} t \right)$ is the returns to scale, calculated as the sum of the output elasticities that characterizes the estimated frontier production function (_ >=< 1.0).

Technical change is a measure of shifts in the production frontier and can be estimated for individual DMUs, or for the industry as a whole. At a given point in time, the most productive DMUs determine the technical frontier. Technical change is the percent growth (or decline) in productivity between the most productive DMUs in time period *t* and the most productive DMUs in time period *t-1*.

Efficiency change is a measure of how well the average DMU is adjusting its production function to the existing state of technology. Under the assumption that (over a sufficiently long time horizon) technology has a positive effect on an industry's productivity growth, efficiency change can be thought of as a measure of how well the typical DMU is doing at "catching up" to the ever-changing state of technology.

Under the assumption of constant returns to scale (CRS), a proportional change in all inputs results in a proportional change in output, and the DMU (or industry) is said to be scale efficient. For the scale efficient DMU, an increase or decrease in the use of inputs will make no contribution to productivity change. That is, under the assumption of CRS, $\hat{\varepsilon} = 1$ and $(\hat{\varepsilon} - 1) \cdot \sum_n \left(\frac{\hat{\varepsilon}_n}{\hat{\varepsilon}} \right) x_n = 0$. Therefore, scale efficiency implies that productivity change is a function of technical change and/or efficiency change.

On the other hand, if the DMU or industry is operating at a point of decreasing returns to scale (DRS), (i.e., $\hat{\varepsilon} < 1$), then $(\hat{\varepsilon} - 1) \cdot \sum_n \left(\frac{\hat{\varepsilon}_n}{\hat{\varepsilon}} \right) x_n < 0$ and the scale inefficiency of the DMU or industry will have a negative effect on productivity change. Conversely, if the DMU or industry is operating at a point of increasing returns to scale (IRS), (i.e., $\hat{\varepsilon} > 1$), then $(\hat{\varepsilon} - 1) \cdot \sum_n \left(\frac{\hat{\varepsilon}_n}{\hat{\varepsilon}} \right) x_n > 0$ and the scale inefficiency of the DMU or industry will have a positive effect on productivity change.

Kumbhakar and Lovell (2000 p284) show that the impact on productivity of the three components is additive. That is,

$$T\dot{F}P = T\Delta + (\varepsilon - 1) \cdot \sum_n \left(\frac{\varepsilon_n}{\varepsilon} \right) \dot{x}_n + TE\Delta . \tag{10}$$

Regularity Conditions

Because of its flexibility, the translog function has become the most common specification for estimating the stochastic production frontier. However, most empirical applications do not test for the regularity conditions of monotonicity, diminishing marginal productivity, and quasi-concavity. Sauer and Hockmann (2005) review eight published studies that estimate a stochastic production frontier using the translog functional form. Sauer and Hockmann (2005) found that monotonicity was violated for at least one input in four of the articles and that diminishing marginal productivity and quasi-concavity were violated in all of the articles.[33] The authors note that although the frontiers possess the desired flexibility, the regularity conditions do not hold (at least at the sample mean) and thus the estimated efficiency scores derived from the functions are not theoretically consistent. More importantly, as Sauer and Hockmann (p14) state, the derived efficiency scores "… are not an appropriate basis for the formulation of policy measures focusing on the relative performance of the investigated decision making units."

Regularity of the estimated production frontier can only be done *a posteriori*, perhaps explaining why this important step is often neglected or not reported.

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[33] Sauer and Hockmann (2005) use the sample mean as their point of approximation for testing the regularity conditions.

Ideally, the regularity conditions should be checked for each data point; if the conditions do not hold, the function should be re-estimated with the conditions imposed. However, doing so for the translog function will result in significant loss of flexibility, thus, eliminating its validity as a flexible functional form.[34] Hence, regularity conditions are almost never examined globally for translog or other functions. Instead, the function is checked at a point or a set of points of approximation, generally the sample mean. This is the process followed here.

Monotonicity

For a production function to be a monotonic function, all inputs must have non-negative marginal products,

$$\partial y / \partial x_i \geq 0 . \tag{11}$$

The marginal productivity of an input is always non-negative, and thus a small increase in the quantity of an input used in a production process cannot lead to a decrease in the amount of output produced.

Diminishing Marginal Productivity

The law of diminishing marginal productivity states that as the use of an input increases, holding all other inputs constant, the associated marginal increase in production cannot increase. With a twice, continuously differentiable function, such as the translog, diminishing marginal productivity implies:

$$\partial^2 y / \partial x_i^2 \leq 0 . \tag{12}$$

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[34] A valid flexible form must contain at least _(k + 2)(k + 1) independent parameters. As Diewert and Wales (1987) discuss, a potentially serious problem associated with imposing global curvature conditions on the translog function is the destruction of the function's flexible property. The translos is only assured to be a second-order approximation at one point.

Chambers (1988 p12) makes two notes related to equation 12. First, equation 12 rules out the possibility of increasing marginal productivity occurring in the first region of production. This is justified on the basis that production in the first region is not economically feasible (at least in the long run). Second, economists typically assume that equation 12 only holds within a restricted region of the production function and one should not assert that it applies everywhere.

Quasi-Concavity

The condition of quasi-concavity is directly tied to the condition of convexity of the input requirement set.[35] Simply put, convexity of the input requirement set implies that if x_1 and x_2 can produce y, then any weighted average (i.e., "convex combination") of these two inputs can also produce y (Chambers 1988 p10). Meeting the conditions of quasi-concavity implies that the input requirement set is convex. Quasi-concavity is relatively simple to determine via the Hessian matrix, derived from the second-order derivatives of the translog production function,

$$H = \begin{bmatrix} f_{11} & f_{12} & f_{13} & f_{14} \\ f_{21} & f_{22} & f_{23} & f_{24} \\ f_{31} & f_{32} & f_{33} & f_{34} \\ f_{41} & f_{42} & f_{43} & f_{44} \end{bmatrix},$$

where

H denotes the Hessian matrix;

$f_{ii} = \partial^2 y / \partial x_i^2 \, , i = 1,\ldots,4 \,;$

$f_{ij} = \partial^2 y / \partial x_i x_j \, , i = 1,\ldots,4;\ j = 1,\ldots 4; i \neq j;\ f_{ij} = f_{ji} \, .$

[35] The input requirement set is the set of all combinations of inputs capable of producing a given level of output.

The necessary and sufficient conditions for quasi-concavity of the production function (at the point(s) of approximation) require that H be negative semi-definite.[36]

Substitution Between Inputs

The degree of substitutability between inputs in response to changes in quantity ratios of inputs is examined through the Morishima elasticity of substitution. The elasticity of substitution, first introduced by Hicks (1932), is a unit-free measure of the substitutability between inputs. It represents a measure of the curvature of the isoquant describing the relationship between inputs i and j. Although there are several alternative measures of the degree of substitutability between inputs, only the Morishima elasticity of substitution is considered in this study. Chambers (1988 p35) shows that the Morishima elasticity of substitution can be derived from components of the estimated production function.

$$\sigma_{ij}^{M} = \frac{f_j}{x_i}\frac{F_{ij}}{F} - \frac{f_j}{x_j}\frac{F_{ij}}{F}, \tag{11}$$

where F is the determinant of the bordered Hessian:

$$F = \begin{vmatrix} 0 & f_1 & f_2 & f_3 & f_4 \\ f_1 & f_{11} & f_{12} & f_{13} & f_{14} \\ f_2 & f_{21} & f_{22} & f_{23} & f_{24} \\ f_3 & f_{31} & f_{32} & f_{33} & f_{34} \\ f_4 & f_{41} & f_{42} & f_{43} & f_{44} \end{vmatrix}, \text{ and}$$

F_{ij} is the cofactor associated with f_{ij} $(F_{ij} = F_{ji})$

f_j is the marginal product of input j $\left(f_j = \partial y / \partial x_j\right)$;

[36] Negative semi-definiteness is determined by checking each of the four determinants of H. The determinants should alternate in sign, beginning with negative.

x_i is the mean value of input *i*

x_j is the mean value of input *j*.

The Morishima elasticity was selected over the Allen elasticity because, as stated in Chambers (1988 p96), the Morishima elasticity is a much more economically relevant concept than the Allen elasticity, since it is an exact measure of how the *i* and *j* input ratio responds to a change in the price of *j* ($i \neq j$).[37]

Although the vast majority of studies that have examined the substitutability between input factors in the production of lumber have estimated the Allen elasticity, Blackorby and Russell (1989, pp882-883) conclude that the Allen elasticity of substitution is not actually a measure of the ease of substitution or curvature of the isoquant, and that "As a quantitative measure, it has no meaning." The authors conclude that the Allen elasticity is "incrementally" and completely uninformative. Comparatively, Blackorby and Russell (1989 p883) state that the Morishima elasticity of substitution is a measure of the curvature of the isoquant and the ease of substitution, as well as a "…sufficient statistic for assessing—quantitatively and qualitatively—the effects of changes in price or quantity ratios on relative factor shares..."

EMPIRICAL RESULTS

Maximum likelihood estimates of the parameters of the preferred SFPF model were obtained using Limdep 8.0, and are presented in Table 9. Alternative model specifications were considered and are discussed below.

The inclusion of *time* and *time*^{2} in the production function is intended to measure the rate of Hicks Neutral technical change over the three decades of

[37] Note that Chambers (1988 p96) is referring to the derivation of the Morishima from the cost function. With respect to the production function (which does not consider prices), the elasticity of substitution is actually concerned with the response of input *i* to a change in the ratio of *j* and *i*.

data.[38] Likewise, the coefficients on the interaction terms between time and each of the inputs in the frontier production function are intended to measure the rate of biased technical change over the period. The coefficient on time and time^2 are positive and statistically significant, indicating that Hicks neutral technical change occurred over the period.[39] The coefficient on the interaction term between capital and time is of the expected sign and is statistically significant. Technical change in the Northwest sawmill industry has on average been capital-using, growing at a rate of about 1.0% per year. Over this same time, technical change has also been labor saving, with total man hours declining by 0.6% per year. The coefficient estimate on the interaction between time and sawlogs indicates that sawlog-use grew over time by a very small amount. However, the coefficient estimate is not statistically significant. The coefficient estimate for the interaction between time and *other inputs* indicates *other input* usage declined over the study period, however it too is not statistically significant.

Coefficient estimates of the regional dummies (the fixed effects) represent shifts in the y-intersection of the frontier production function. Oregon's Region 4 (central & eastern Oregon) is the base case. The coefficient estimates of the regional dummies for Washington are negative and not statistically significant, indicating the position of the production frontier of these regions is no different than Oregon's Region 4. Conversely, the coefficient estimates on the dummy variable for Oregon's westside regions are positive and statistically significant, indicating their respective production frontiers extend beyond that of Region 4.

Whereas time in the frontier production function captures technical change over time (i.e., shifting of the production frontier), time in the inefficiency

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[38] Technical change is Hicks neutral if it can be shown to be separable from any of the inputs of production.

[39] The coefficient on time is statistically significant at the 0.05 level and the coefficient on time^2 is significant at the 0.10 level.

model is intended to capture efficiency change over time (i.e., changes in the distance of the average DMU from the industry production frontier). The positive sign on the coefficient of the time variable indicates that inefficiency is increasing over time. Likewise, the positive value on the coefficient of the dummy variable for the Oregon regions is also positive, indicating that relative to Washington regions, Oregon regions are on average further from the efficient frontier.[40]

The last four coefficients σ_s, σ_s^2, _, and _ are measures related to the variance of the random variables V_{it} and U_{it}. σ_s and σ_s^2 are, respectively, the standard deviation and variance of the composed error term, and are measures of the total residual of the estimated frontier production function.[41] _ and _ are measures of the relative importance of the inefficiency error.

_ is the ratio of σ_u to σ_v, and is a measure of the relative importance of the inefficiency error. The value of 0.73 _ indicates that less than half the composed residual is due to the inefficiency error. _ is a measure of the percent of the composed error that is attributable to the one-sided inefficiency residual.[42] The value of _, 0.35 indicates that only 35% of the total "noise" in the estimation of the stochastic production function is attributable to inefficiency effects. Stated another way, most of the deviation from the efficient frontier is due to random noise. Had the frontier production function been estimated in a deterministic model, all of the residual would have been attributed to inefficiency.

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[40] It is important to remember that the industry is experiencing positive technical change, thus the industry's efficient frontier is expanding. The inefficiency effects model measures changes in the location of the typical DMU relative to the expanding frontier.

[41] $\sigma_s = \left(\hat{\sigma}_u^2 + \hat{\sigma}_v^2\right)^{1/2}$

[42] $\gamma = \sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right)$

The time-varying SFPF model (the “preferred model”) was tested against five alternative specifications. Alternative 1 is the Cobb Douglas specification that includes the four input factors and time. However, this model could not be estimated because the OLS residuals possessed the wrong skew (positive in the case of the frontier production function), indicating that the Cobb Douglas was not the correct specification for the empirical production function[43]. Alternative 2 is a three-input translog production function that excludes *other inputs*, but is otherwise identical to the preferred model. Alternative 3 has the same specification for the production function and inefficiency effects equation as the preferred model, however it also includes four additional interaction variables: *capital*other*, *labor*other*, *sawlogs*other*, *other*other*. Alternative 4 is a four-input translog production function that excludes Hicks neutral and biased technical change. Alternative 5 has the same production function specification as the preferred model, but does not explicitly model inefficiency effects. Finally, Alternative 6 has the same specification for the production function and inefficiency effects equation as the preferred model, but excludes the fixed effects for the sawmill regions.

Likelihood ratio tests were used to test the above specifications and are reported in Table 10. All tests were conducted at the 0.05 level of significance. As stated above, the Cobb Douglas model could not be estimated, so the likelihood ratio test could not be performed. For Alternative 2, the likelihood ratio was 63.6, indicating rejection of the null hypothesis that all the coefficients on “other” were equal to zero. Alternative 3 is the only likelihood ratio test in which the null hypothesis is not rejected (LR = 1.7 vs. critical

[43] As discussed previously, the error term of the stochastic production function is composed of v_i, the symmetric random noise component, and u_i, the non-negative technical inefficiency component. The error term $\varepsilon_i = v_i - u_i$ is negatively skewed because $u_i > 0$, under the assumption that the stochastic production function contains technical inefficiency effects. Prior to estimation of the stochastic production function model using maximum likelihood methods, the model is estimated using OLS and the presence of technical inefficiency in the data is tested. If $\varepsilon_i \geq 0$, then either the data do not support the estimation of the stochastic production function, or the model is misspecified.

value of 9.49). This result provides statistical evidence that the production relationship is better represented without the additional interaction terms involving "other" inputs. There was sufficient evidence to reject the null hypothesis represented by Alternative 4 that neither Hicks neutral, nor biased technical change occurred over the study period (likelihood ratio = 77.6). For Alternative 5, the likelihood ratio test was 52.7, thus rejecting the null hypothesis that the explanatory variables in the inefficiency model are jointly insignificant, despite the fact that none of the explanatory variables are individually statistically significant. Finally, the likelihood ratio for Alternative 6 (104.7) indicates there is sufficient evidence to reject the null hypothesis that the coefficients on the fixed effects are equal to zero.

Regularity Conditions

Table 11 shows the results of the examination of the conditions of monotonicity and diminishing marginal productivity at the mean of the data. The marginal product of each of the four inputs is positive, with sawlogs and *other* being significantly different from zero. Each of the marginal products is also decreasing in inputs, implying diminishing marginal productivity. The standard errors on labor, sawlogs, and *other inputs* are statistically significant at the 0.01 level. The fact that the marginal product estimates for capital are of the correct sign, but are not statistically significant, implies that the industry generally operated with at least a small amount of excess capacity.[44]

Building the Hessian matrix for the production function in the same order as the inputs are listed above, results in the following determinants, which show the matrix to be negative semi-definite at the sample means.

$$H_1 = \left[f_{cc} \right] = -8.97\text{e}-06$$

[44] That is, a small percentage increase in capacity, holding all other inputs constant, would not lead to an increase in output.

$$H_2 = \begin{bmatrix} f_{cc} & f_{cl} \\ f_{lc} & f_{ll} \end{bmatrix} = 1.5\text{e} - 017$$

$$H_3 = \begin{bmatrix} f_{cc} & f_{cl} & f_{cw} \\ f_{lc} & f_{ll} & f_{lw} \\ f_{wc} & f_{wl} & f_{ww} \end{bmatrix} = -2.22\text{e} - 020$$

$$H_4 = \begin{bmatrix} f_{cc} & f_{cl} & f_{cw} & f_{co} \\ f_{lc} & f_{ll} & f_{lw} & f_{lo} \\ f_{wc} & f_{wl} & f_{ww} & f_{wo} \\ f_{oc} & f_{ol} & f_{ow} & f_{oo} \end{bmatrix} = 1.14\text{e} - 025$$

Output Elasticities and Productivity Growth

Table 12 presents the elasticity of output for each input, the returns to scale, and estimates of technical change, efficiency change, and productivity change. These measures were estimated at the mean of the entire sample and at the mean of each decade of the study period.[45] With two exceptions, all of the output elasticities have the expected sign. The exceptions, the estimated elasticities on capital for the 1970s and labor for the 1990s, are negative, but are not statistically significant. The output elasticity of capital evolves from being negative and not statistically significant for the 1970s, to being positive, but not statistically significant for the 1980s, and finally to being positive and statistically significant for the 1990s.

The time path for the output elasticity of labor is the opposite of that for capital. For the 1970s, the output elasticity of labor is positive and statistically significant; for the 1980s it is positive, but not statistically significant; for the 1990s, it is neither positive, nor statistically significant. These results are consistent with anecdotal evidence of increasing automation in the sawmill industry and the highly publicized declines in forest industry employment that occurred throughout the latter-half of the study period.

[45] Data for the State of Washington for 2000 and 2002 were included in the 1990 estimates.

Changes in the elasticity of output with respect to capital and with respect to labor are also consistent with the coefficient estimates on the capital-time and labor-time interaction variables in the estimated production function (0.0107 and -0.006, respectively). Technical change has been both capital-using and labor-saving. As the sawmill industry adopted greater and greater productivity-enhancing technology, the sensitivity of lumber production to a small change in labor declined from 0.13 in the 1970s to zero in the 1990s. Comparatively, the output elasticity with respect to capital grew from zero in the 1970s to 0.16 in the 1990s.

The output elasticity with respect to sawlogs increased in magnitude over the period, and was statistically significant at the mean value for each decade. The impact on lumber production from a marginal increase in sawlogs, holding all other inputs constant, increased from 0.58 for the 1970s to 0.73 for the 1990s. Nevertheless, the estimated output elasticity for each decade is within the 95% CI of the output elasticity for the other decades. The output elasticity on *other inputs* declined in magnitude from decade to decade, and was statistically significant for each decade.

Estimates of the returns to scale in the Northwest lumber industry grew from 0.98 for the 1970s to 1.07 for the 1990s, indicating changes in scale efficiency over the three decades. However, given the standard error on each estimate, the assumption of constant returns to scale cannot be rejected for the overall sample, or for any of the individual decades. It is unclear how estimates of returns to scale at the regional level can be extrapolated down to the firm level.

The last four rows of Table 12 show estimates of technical change, efficiency change, and productivity change for each decade and for the entire sample. Productivity change is a measure of the percent increase in output for a fixed level of inputs. Productivity is composed of technical change, efficiency change, and changes in scale efficiency. Technical change represents movement (generally outward) of the industry's production frontier; efficiency change represents change in the position of the average DMU relative to the production frontier. Efficiency change is a measure of a DMU's progress (or regress) at incorporating the industry's available technology into its own production function. Efficiency change is often referred to as the "catching-up" effect, when a DMU is nearer the production frontier in time period $t+1$ than it was in time period t. Scale efficiency change is a measure of movement of a DMU's operation either toward or away from its technically optimum scale (Coelli et al., 2005 p75).

The results of the analysis indicate that substantial technical change occurred throughout the study period. For the 1970s, technical change grew on an average annual basis by 1.6%. For the 1980s and 1990s, the rate of change was even greater (2.1% and 2.2% per year). As the efficient frontier expanded during the 1970s, 1980s, and 1990s, the distance of the average DMU from the efficient frontier also increased, but only slightly. For the 1970s, the rate of efficiency change was very slight, averaging only -0.02% per year. The rate of change increased to -0.28% per year for the 1980s, and to -0.033% per year in the 1990s. The most obvious explanation for this seemingly contradictory phenomenon is that some DMUs were the leaders in adopting productivity-enhancing technologies, and thus pushed out the industry's production frontier. For the other DMUs, the adoption of the new technologies was not immediate, so distance from the production frontier increased. The point estimates of scale efficiency change were very small and positive in each decade, but were not significantly different from zero.

Productivity growth (TFP change) is the sum of technical change, efficiency change, and scale efficiency.[46] The rate of productivity growth during the study period closely mirrors the rate of technical change and is presented in

[46] If technical efficiency is assumed time invariant, then productivity growth reduces to technical change plus scale efficiency.

Table 12, both exclusive of and including efficiency change.[47] Excluding the effects of efficiency change (or alternatively assuming time-invariant technical efficiency), productivity growth averaged 1.6% per year in the 1970s, 2.1% in the 1980s, and 2.4% during the 1990s. For the entire period, the average annual technical change was 2.0%. Including the effects of efficiency change (last row of Table 12), the estimates of productivity were similar, but slightly lower.

Elasticity of Substitution

The Morishima elasticity of substitution is a measure of the response of input *i* to a change in the ratio of inputs *i* and *j*, and represents movement along the isoquant. Unlike the Allen partial elasticity of substitution, the Morishima elasticity of substitution is not symmetric. The response of input *i* to a change in the ratio of the *i* and *j* inputs is not constrained to equal the response of input *j* to a change in the *j* and *i* input ratio ($\sigma_{ij}^{M} \neq \sigma_{ji}^{M}$). Table 13 shows for each pair of inputs, the ability of input *j* to substitute for input *i*.[48]
Considering first the relationship between labor and capital, Table 13 shows that labor is not substitutable for capital, but capital is substitutable for labor. Thus, a change in the input ratio of capital to labor would have no impact on the usage of labor, but a change in the input ratio of labor to capital would result in a change in the use of capital relative to labor. The substitutability of capital for labor observed for each decade of the study period allowed labor productivity to increase, but at the cost of decreasing employment in the

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[47] Efficiency change is calculated outside of the model based on the estimated technical efficiencies. Only point estimates were calculated. Horrace and Schmidt (1996) propose a method for constructing confidence intervals for estimates of efficiency change derived from panel data models. Because of the very small size of the efficiency estimates calculated in this analysis (i.e., smaller than standard errors of the technical change estimates), confidence intervals were not computed.

[48] $\sigma_{ij}^{M} < 0$ indicates that with respect to input *i*, the inputs are Morishima complements;
$\sigma_{ij}^{M} > 0$ indicates that with respect to input *i*, the inputs are Morishima substitutes;
$\sigma_{ij}^{M} = 0$ indicates that with respect to input *i*, the inputs are Leontief (i.e., fixed factor).

sawmilling industry. These findings appear to support Stier's (1980) observation that future growth in lumber production by Northwest sawmills would generate only small increases in employment.

A similar relationship exists between labor and sawlogs. A change in the input ratio of sawlogs to labor would have no effect on the usage of labor $(\sigma_{W,L} = 0)$, but a change in the input ratio of labor to sawlogs would result in the substitution of sawlogs for labor. However, this result is not consistent across the three decades of analysis. For the 1970s, labor and sawlogs are Morishima complements (with respect to a change in the relative price of labor), thus an increase in the relative price of labor would result in less of both inputs being used.

A change in the input ratio of *other inputs* to labor would also have no effect on the usage of *other inputs*, but the two are Morishima complements when considering a change in the input ratio of other inputs to labor.

The input-substitution relationship between sawlogs and capital is also of particular importance. With respect to an increase in the relative price of capital, the two inputs are Morishima complements, although the degree to which this is the case has changed over the study period. In the 1970s, sawlogs and capital were also Morishima complements with respect to an increase in the relative price of sawlogs, but they were not strongly complementary. This relationship has changed and now capital is weakly substitutable for sawlogs.

Comparison of the estimated elasticities of substitution to other studies is difficult. Most previous studies estimate only Allen elasticities, which are not directly comparable to the Morishimo measure. Three relatively recent analyses which report Morishima elasticites are Puttock and Preston (1992), Baardsen (2000), and Latta and Adams (1999).

Puttock and Preston (1992) estimated Morishima elasticities for Ontario hardwood sawmills based on a translog cost function, which included three inputs: sawlogs, labor, and energy. Data on 21 mills were observed between 1980 and 1984 and the authors estimated Morishima elasticities for each pair of inputs. However, the authors seemingly assumed the Morishima elasticity to be symmetric and computed only one estimate for each input pair. Therefore, their estimate of the elasticity of substitution for labor and sawlogs (0.595) is difficult to compare to those estimated in this study because it is unclear as to whether they report $\sigma^M_{L,W}$ or $\sigma^M_{W,L}$. Even without this inconsistency in their reported results, meaningful comparison is difficult because of the very short time-span of their data, relative to this study, and because the majority of lumber production in the Northwest is softwood, while Puttock and Preston (1992) consider hardwood.

Using a very large panel data set of individual Norwegian sawmills, Baardsen (2000) derives Morishima elasticities from an 8-input translog cost function. Included within the eight inputs are sawlogs, labor, and capital which correspond to sawlogs, labor, and capital in the present analysis, as well as other materials, electricity, fuel oil, and other inputs, which correspond to *other* in the current analysis. For each of the elasticities of substitution of greatest interest to this study, Baardsen (2000) finds the pairs of inputs to be substitutes.

Latta and Adams (1999) employ a normalized, restricted profit function to estimate various economic measures for three regions of Canada's softwood lumber industry: the British Columbia Coast (BCC), the British Columbia interior and Alberta (INT), and the rest of Canada (EAST). The authors formulate a three-input production process (softwood sawlogs (W), labor (L), and other inputs) that produces a single output (lumber + chips). Latta and Adams examine the Morishima elasticity of substitution between labor and sawlogs and find them to be substitutes and statistically significant in BCC and INT. For the EAST, they find that $\sigma^M_{L,W} > 0$ and $\sigma^M_{W,L} \leq 0$, but neither estimate is statistically significant.

Technical Efficiency

The estimates of technical efficiency are high over the entire study period for all regions (see Table 14).[49] The technical efficiency results are especially high through the mid 1980s and are strikingly similar to the results obtained by Yin (2000) in his study of global pulp producers. Perhaps the high efficiency estimates in this study should not come as a surprise, considering that there are only nine regions and for many years there are data for only five regions. The paucity of data for any one year results in estimated production frontiers with limited ability to discriminate, as most of the DMUs are needed to construct the frontier. This is a substantial limitation of this data set when considering results in the cross-section, but should not affect the reliability of estimates of technical change or productivity growth over time.

The descriptive statistics in Table 14 show that the average, relative technical efficiency declined over the study period, from essentially 1.0 in 1968 to 95.5 in 2002. Over the same period, the minimum estimated technical efficiency declined from 0.993 to 0.926, whereas the maximum declined very little (from 0.997 to 0.981). The greater spread between the minimum and maximum efficiency scores indicates heterogeneity between the regions increased over the three decades of analysis. Figure 8 shows the increasing heterogeneity more clearly. During the first decade of data (1968-1980), there was little variability in the estimated technical efficiency scores of the nine regions. This changed in the early 1980s as the distribution of technical efficiency scores widened and the average score declined.

Taking a closer look at the data, Table 15 shows the geometric mean technical efficiency estimates for Oregon (4 regions), Washington (5 regions), the Eastside (4 regions), and the westside (5 regions).[50] Regardless of how the

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[49] The measures of technical efficiency are equal to $e^{-u_{it}}$, where u_{it} is the estimated one-side inefficiency error for *i-th* DMU in time period *t*.

[50] Note: these are not mutually exclusive aggregations.

regions are aggregated, technical efficiency declined over the study period. The degree to which technical efficiency declined varied considerably between the two states, with the Oregon regions declining much more than the Washington regions. The decline in the relative technical efficiency of Oregon lumber producers may indicate a persistent difference in sawlog supply, management effectiveness, innovation, or investment, relative to Washington mills. Nevertheless, it should be remembered that the estimates of technical efficiency are relative to the position of the industry production frontier at a specific point in time. Even as the relative technical efficiency of Oregon producers appears to decline over time, the production frontier, to which technical efficiency is measured, is shifting out. Thus, Oregon sawmills are also experiencing technical progress and productivity growth, but seemingly at a slower rate than Washington mills.

DISCUSSION

Analysis of more than three decades of production data for the Pacific Northwest sawmilling industry reveals that lumber producers in Oregon and Washington experienced substantial productivity gains. The vast majority of these gains were due to technical change (i.e., expansion of the industry's production frontier). The statistical evidence indicates that scale efficiency played no role in productivity growth, and efficiency change had a very small, but negative effect on productivity growth.[51] Negative efficiency change indicates that, even as the industry's production frontier expanded over time, the distance of the average DMU to the industry's production frontier actually increased. The result is that, even though all regions experienced technical change and productivity growth over the study period, some regions experienced less than others.

Under the assumptions that (1) individual mills are price takers in the output market and (2) there are substantial opportunities for arbitrage in the input

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[51] Statistical results were not computed for the efficiency change estimtes.

markets, mills are not only competing with other lumber producers within their same region, but are also competing with mills throughout the Northwest. The result is that as technical innovation allowed the most innovative mills to push out the industry's production frontier, other Northwest mills were forced to adopt productivity-enhancing technology in order to keep up with the expanding frontier, or shut down. A portion of the productivity growth observed over the study period may be due to the least technically efficient firms shutting down, thus resulting in efficiency change and productivity growth through attrition (Stevens 1991).[52] Estimates of technical efficiency are high for all regions for all time points (> 0.89). The high technical efficiency scores are due in part to the small number of DMUs, but may also be due to rapid transfers of technology and innovation between sawmills in the Northwest, thus resulting in little variation in technical efficiency between the sawmilling regions.

The results of this analysis indicate that over the 34-year study period, technical change was labor-saving and capital-using, and was neutral with respect to sawlog usage. Neutral technical change in sawlog usage may be contrary to one's *a priori* assumption that technical change would be wood-saving, due to the adoption of sawing technologies that are capable of increasing yields per unit of sawlog input (Stier and Bengston 1992). Results from the empirical literature are mixed on this issue. Abt (1987) reports wood-using bias for Pacific Northwest sawmills over the period 1963-1978. Martinello (1987) found that technical change was neutral with respect to sawlog usage for coastal British Columbia (BC), but technology was wood-saving for interior BC. Analyzing data from 1957-1981 for the U.S. Pacific Northwest and BC, Constantino and Haley (1988) found that technical change was both labor- and wood-saving. Meil and Nautiyal (1988) found that with

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[52] Stevens states, "When the closure of older, less (sic) labor-intensive mills is permanent then *technological* change through attrition takes place." In fact, the closure of older, more labor-intensive mills leads to *efficiency* change in the industry. That is, the industry's production frontier is not shifted out by the closure of the older, more labor-intensive mills, but rather the average proximity to the frontier of the remaining mills is reduced.

few exceptions, technical change was labor-saving and sawlog using for the major lumber producing regions of Canada.

The lack of consensus in the literature on the existence and direction of technical bias with respect to sawlog usage may be due to the spatial and temporal heterogeneity of sawlogs. That is, sawlog size and quality vary across space and time. In the Northwest, average sawlog diameter decreased through the 1970s, 1980s, and 1990s, and it is generally agreed that sawlog quality declined over this period. The trend toward smaller sawlogs has led to increased productivity because the milling of small logs is less labor intensive and more amenable to mechanization. Consist with decreases in the size and quality of sawlogs over the past few decades has been a decrease in lumber quality. This is not captured in the analysis. The average quality of labor has likely also changed as many unskilled workers have been displaced due to changes in technology.

This study is the first to utilize a stochastic frontier production function to examine productivity growth, technical change, and other economic measures of the Northwest sawmilling industry. SFA methods allows for the relaxation of the assumptions that lumber producers are successful cost minimizers and/or profit maximizers. Instead of estimating the average production function and assuming deviations from this function (either positive or negative) are simply random disturbance, SFA estimates the production frontier and provides estimates of each DMU's inefficiency, relative to the estimated frontier. This study is also the first in more than a decade to examine the technical structure of the Oregon and Washington lumber producing industry, and to examine changes in that structure. Despite substantial declines in harvest on Northwest National Forests over the past two decades, Oregon is still the largest lumber producing state in the U.S. and Washington produces more lumber today than it did in the 1970s, 1980s, or 1990s. Strong productivity growth over the last three decades has helped NW lumber producers remain competitive in an ever-increasing global marketplace.

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Table 8: Summary Statistics for Variables in the Stochastic Frontier Production Function

Variable	Mean	St. Dev.	Median	Min.	Max.
Lumber Production (MBF lumber tally, softwood + hardwood)	1,020,347	945,315	527,840	136,030	3,706,856
Sawlogs (MBF Log Scale)	694,017	635,217	361,980	89,957	2,683,044
8-Hour Capacity (MBF Lumber Tally)	3,152	2,876	1,760	365	11,675
Labor (Thousands of Total Person Hours)	12,966	13,336	7,148	1,148	57,510
Other (Energy & Supply Costs in Thousands of 1970 Dollars)	7,515	6,829	4,268	893	28,020

Table 9: Estimation Results of Preferred SFPF and Inefficiency Effects Model

Variable	Coefficient	Standard Error	t-ratio	P-value
Constant	-11.4480	5.9507	-1.924	0.054
Capital	-0.1933	0.8650	-0.223	0.823
Labor	2.3301	1.0647	2.189	0.029
Sawlogs	-1.8022	1.4006	-1.287	0.198
Other	0.3796	0.0859	4.420	0.000
Capital _ Capital	-0.0452	0.1459	-0.310	0.757
Labor _ Labor	-0.2266	0.1046	-2.166	0.030
Sawlogs _ Sawlogs	-0.2722	0.1954	-1.393	0.164
Capital _ Labor	0.0049	0.0774	0.064	0.949
Capital _ Sawlogs	0.0504	0.1485	0.339	0.734
Labor _ Sawlogs	0.2286	0.1378	1.659	0.097
Time	0.0419	0.0168	2.498	0.013
Time _ Capital	0.0107	0.0025	4.191	0.000
Time _ Labor	-0.0060	0.0019	-3.207	0.001
Time _ Sawlogs	0.0049	0.0047	1.043	0.297
Time _ Other	-0.0054	0.0046	-1.187	0.235
Time _ Time	0.0004	0.0002	1.697	0.090
Region 1 (Western WA)	-0.1085	1.1237	-0.097	0.923
Region 2 (Western WA)	-0.1896	1.1465	-0.165	0.869
Region 3 (Central WA)	-0.1905	1.1195	-0.170	0.865
Region 4 (Central WA)	-0.2362	1.1192	-0.211	0.833
Region 5 (Eastern WA)	-0.1958	1.1217	-0.175	0.861
Region 6 (Western OR)	0.1951	0.0288	6.774	0.000
Region 7 (Western OR)	0.2472	0.0356	6.954	0.000
Region 8 (Eastern OR)	0.1834	0.0509	3.603	0.000
Parameters in One-Sided Inefficiency Model				
Constant	-0.2517	0.3671	-0.686	0.493
Time	0.2943	1.1433	0.257	0.797
Oregon Indicator	0.0171	0.9579	0.018	0.986
Variance Parameters for Compound Errors				
Lambda $(\lambda = (\sigma_u / \sigma_v))$	0.7316	0.5141	1.423	0.155
Gamma $(\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2))$	0.3487			
Sigma $(\sigma_s = sqrt(\sigma_u^2 + \sigma_v^2))$	0.0390	0.0037	10.621	0.000
Sigma-square (σ_s^2)	0.0015	0.0003	5.314	0.000
Log Likelihood Function	237.79			

Table 10: Likelihood Ratio Tests

Variable	Log Likelihood	Likelihood Ratio Test Statistic	Critical Value (_ = 0.05)	Decision
Preferred Model: 4-input translog (with time-varying technical change & inefficiency effects model)	237.79			
Alternative 1: 4-input Cobb Douglas H_0: $\_{ij} = 0$, $i \le j$ = sawlogs, labor, capital, other, time	OLS residuals have wrong skew. OLS is MLE. Reject H_0. Cobb-Douglas is not correct Specification			Reject H_0
Alternative 2: 3-input translog H_0: $\_{i} = \_{i,t} = 0$; i = other; t = time	206.00	63.59	5.99	Reject H_0
Alternative 3: 4-input translog with "other" interactions Ho: $\sum \beta_{ij} = 0$; i = other; j = capital, labor, sawlogs, other	236.94	1.70	9.49	Fail to Reject H_0
Alternative 4: 4-input translog with NO technical change H_0: $\_{t} = \_{tt} = \_{it} = 0$; i = sawlogs, labor, capital, other	198.98	77.62	12.59	Reject H_0
Alternative 5: 4-input translog without explanatory variables for inefficiency effects H_0: $\_{0} = \_{1} = \_{2} = 0$	211.44	52.70	7.81	Reject H_0
Alternative 6: 4-Input translog without fixed effects H_0: $\_{1} = \ldots = \_{8} = 0$	185.46	104.66	15.51	Reject H_0

Table 11: Results of Tests for Monotonicity and Diminishing Marginal Productivity

Input	Monotonicity		Diminishing Marginal Productivity	
	Marginal Product	St. Error	_(Marginal Product)	St. Error
Capital	1.36E-02	1.75E-02	-8.97E-06	1.60E-05
Labor	3.83E-06	3.69E-06	-1.67E-12	6.05E-13
Sawlogs	9.59E-01	9.43E-02	-1.96E-03	4.07E-04
Other	3.85E-02	6.02E-03	-5.13E-06	8.00E-07

Table 12: Elasticities of Mean Output, Returns to Scale, Technical Change, Efficiency Change, and Total Factor Productivity Growth[1]

Input	1970s	1980s	1990s[2]	All Years
Capital	-0.079 *0.067*	0.043 *0.054*	0.161 *0.054*	0.042 *0.054*
Labor	0.127 *0.053*	0.053 *0.048*	-0.038 *0.050*	0.049 *0.047*
Sawlogs	0.584 *0.097*	0.651 *0.061*	0.727 *0.074*	0.652 *0.064*
Other	0.349 *0.065*	0.282 *0.045*	0.221 *0.074*	0.284 *0.044*
Returns To Scale[3]	0.981 *0.041*	1.029 *0.040*	1.071 *0.037*	1.027 *0.039*
Technical Change (Avg. Annual Change)	0.016 *0.003*	0.021 *0.003*	0.022 *0.004*	0.020 *0.003*
Efficiency Change (Avg. Annual Change)	-0.0002	-0.0028	-0.0033	-0.0021
	Point Estimates Only			
Scale Efficiency Change	0.0003 *0.0008*	0.0001 *0.0004*	0.0018 *0.0017*	0.0002 *0.0005*
TFP Change (Excluding Efficiency Change)	0.016 *0.003*	0.021 *0.003*	0.024 *0.005*	0.020 *0.003*
TFP Change (including Efficiency Change)	0.016	0.019	0.021	0.018
	Point Estimates Only			

1. Asymptotic standard errors in *italics*.

2. The "1990s" actually spans the period 1990 – 2002. Only data for Washington were available for 2000 and 2002.

3. At the 0.05 level of significance, constant returns to scale can not be rejected for any period analyzed.

Table 13: Morishima Elasticity of Substitution Between Inputs

Substitution	1970s	1980s	1990s	All Years
Labor for Capital (_C,L)	0.001	0.000	0.000	0.000
Capital for Labor (_L,C)	3.872	0.820	1.516	0.909
Sawlogs for Labor (_L,W)	-6.863	4.661	4.377	5.035
Labor for Sawlogs (_W,L)	0.000	0.000	0.000	0.000
Sawlogs for Capital (_C,W)	-5.233	-0.366	-1.540	-0.476
Capital for Sawlogs (_W,C)	-0.174	0.004	0.067	0.007
Other for Labor (_L,O)	-0.952	-0.891	-0.840	-0.846
Labor for Other (_O,L)	0.000	0.000	0.000	0.000
Other for Capital (_C,O)	0.343	0.163	0.151	0.186
Capital for Other (_O,C)	0.179	-0.041	-0.298	-0.066
Other for Sawlogs (_W,O)	0.339	0.241	0.173	0.239
Sawlogs for Other (_O,W)	-5.302	-5.233	-7.833	-5.942

Table 14: Descriptive Statistics of Estimated Technical Efficiencies

YEAR	Geometric Mean	Standard Deviation	Minimum	Maximum	Median
1968	0.995	0.001	0.993	0.997	0.995
1970	0.996	0.000	0.995	0.996	0.996
1972	0.993	0.004	0.987	0.996	0.995
1974	0.995	0.001	0.995	0.996	0.995
1976	0.993	0.004	0.986	0.996	0.996
1978	0.995	0.000	0.995	0.996	0.995
1980	0.995	0.000	0.995	0.996	0.995
1982	0.980	0.018	0.955	0.996	0.994
1984	0.995	0.001	0.993	0.996	0.995
1985	0.957	0.007	0.952	0.967	0.955
1986	0.994	0.001	0.993	0.995	0.994
1988	0.966	0.031	0.921	0.994	0.990
1990	0.990	0.002	0.986	0.992	0.991
1992	0.952	0.042	0.901	0.993	0.983
1994	0.945	0.044	0.896	0.987	0.981
1996	0.974	0.009	0.964	0.987	0.971
1998	0.939	0.040	0.896	0.981	0.961
2000	0.960	0.008	0.952	0.973	0.956
2002	0.955	0.023	0.926	0.981	0.958

Table 15: Geometric Mean Technical Efficiency Estimates for Oregon, Washington, Eastside, and Westside

Year	Oregon	Washington	Eastside	Westside
1968	0.994	0.995	0.995	0.995
1970	0.994	0.996	0.996	0.996
1972	0.989	0.995	0.993	0.992
1974	NA	0.995	0.996	0.995
1976	0.989	0.996	0.994	0.992
1978	NA	0.995	0.995	0.995
1980	NA	0.995	0.996	0.995
1982	0.961	0.995	0.989	0.973
1984	NA	0.995	0.995	0.995
1985	0.957	NA	0.984	0.973
1986	NA	0.994	0.995	0.993
1988	0.935	0.992	0.977	0.957
1990	NA	0.990	0.992	0.988
1992	0.910	0.987	0.963	0.943
1994	0.899	0.983	0.960	0.933
1996	NA	0.974	0.974	0.973
1998	0.898	0.973	0.953	0.928
2000	NA	0.960	0.957	0.964
2002	NA	0.955	0.941	0.978

Figure 7: Pacific Northwest Sawmill Regions

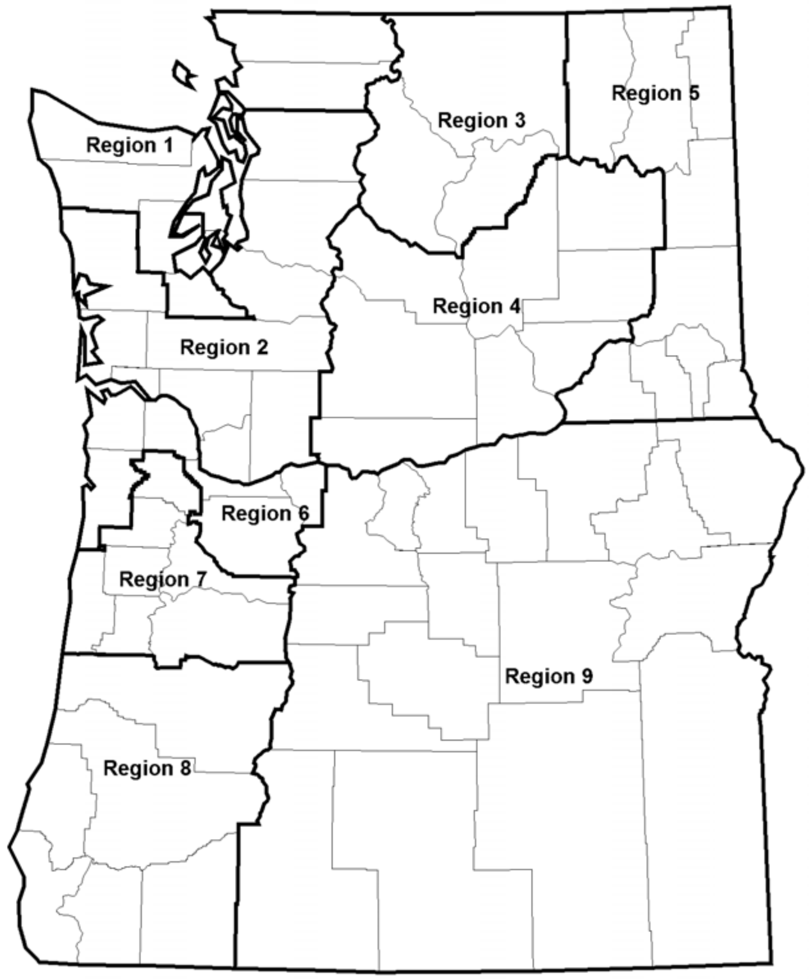
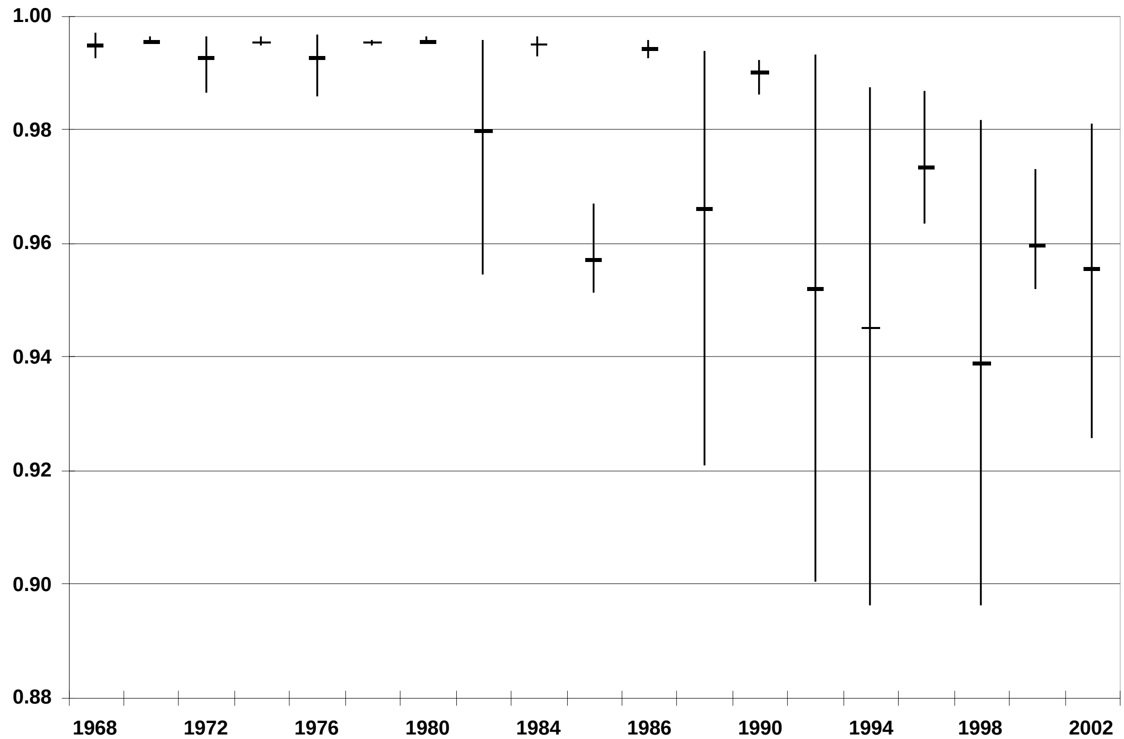


Figure 8: Distribution of Technical Efficiency Estimates, High, Low, and Geometric Mean



Productivity and Efficiency Analysis of the Northwest Sawmill Industry Using Data Envelopment Analysis

Ted L. Helvoigt

Productivity and Efficiency Analysis of the Northwest Sawmill Industry Using Data Envelopment Analysis

Introduction

Changes in the supply of timber from private and public lands in the Pacific Northwest and ever increasing globalization have resulted in a forest products industry in the Northwest that looks much different today than it did 30 years ago. There are fewer sawmills in the Northwest today; the mills today are larger, more automated, and, based on anecdotal evidence, more productive than their predecessors . Although its relative importance has shrunk over the past few decades, the forest products industry continues to be an important part of the economy and culture of the Northwest. The purpose of this analysis is to examine how the structure of the industry has changed over the past few decades.

In this paper data envelopment analysis (DEA) is used to approximate the production frontier of the sawmill industry in the U.S. Pacific Northwest (PNW or NW), comprising Oregon and Washington. Utilizing data that extend from 1968 through 2002, technical efficiency, productivity growth, technical and efficiency change, and returns to scale in the Northwest sawmill industry are estimated. In addition, using methods described by Simar and Wilson (1998, 1999, 2000a, 2000b, 2002), confidence intervals are developed using a bootstrap technique. The data used in this analysis were also used in Chapter 3 to estimate a stochastic frontier production function (SFPF). Estimates of technical efficiency, productivity growth, and technical and efficiency change developed in Chapter 3 are compared in this study to estimates obtained through DEA.

DEA models measure efficiency relative to a non-parametric estimate of the true efficient frontier. The estimated frontier is constructed based on the coordinates in input-output space of the most technically efficient decision making units (DMUs). In DEA, the technical efficiency of a DMU is estimated based on a frontier of best performing DMUs and hence the technical efficiency estimate is a relative, not absolute, measure. Further, as Simar and Wilson (1998) point out, because the statistical estimators of the estimated frontier are based on finite samples, the corresponding measures of technical efficiency are sensitive to the sampling variations of the frontier obtained.

The observed data are the result of an underlying and unobserved data generating process (DGP) (Simar and Wilson 2000a). DEA and other non-parametric methods offer an advantage over econometric-based techniques since they do not require the imposition of possibly incorrect functional relationships between the inputs and outputs of production. However, this advantage comes at the expense of obtaining "deterministic" results, with unknown or assumed non-existent statistical properties. Because DEA is a deterministic technique, hypothesis testing and other statistical analysis has traditionally not been conducted within a DEA framework. The bootstrapping techniques developed by Simar and Wilson (1998, 1999, 2000a, 2000b, 2002) effectively eliminate this shortcoming.

DATA ENVELOPMENT ANALYSIS IN THE FOREST PRODUCTS INDUSTRY

DEA has become an increasingly popular approach for measuring technical efficiency and productivity change. Gattoufi, Oral, and Reisman (2004) cite more than 1,800 articles since 1951 that have appeared in refereed journals and employ DEA methods. Most of the studies cited by Gattoufi et al. were published during the past two decades. There is a small number of recent studies that employ DEA to analyze technical efficiency and/or productivity growth in the forest products sector. Most of these studies focused on the pulp and paper industry, but a handful of studies have examined technical efficiency in the logging industry, forest management, and the sawmill industry.

Salehirad and Sowlati (2005) examine data on 82 British Columbia (BC) sawmills for the year 2002. Although the authors theorize a production process that uses sawlogs, labor, capital, and energy to produce lumber and chips, they construct their DEA models using only sawlogs and labor as inputs. The authors find that under the assumption of variable returns to scale (VRS), 11 of the 82 mills are technically efficient and the average technical efficiency of all mills is 83%. Under the alternative assumption of constant returns to scale (CRS), only 6 mills are technically efficient and the average technical efficiency is 80%. The authors compute scale efficiency and find it to be 0.97. They do not, however, go on to determine if the scale inefficiency measure is statistically different from 1.0. The authors do report that about half of the scale inefficient lumber producers were operating at a point of increasing returns to scale and that the other half at a point of decreasing returns to scale. They conclude from this that in general BC sawmills have a VRS production function.

Nyrud and Baardsen (2002) examine technical efficiency and productivity growth in the Norwegian sawmilling industry over the period 1974-1991. The authors rely on an unbalanced panel data set of 1,320 observations that includes information on 220 individual sawmills. Of these, 66 sawmills remained in business throughout the study period and, therefore, these mills were used to investigate productivity change. The authors divide the 18 years of data into six 3-year periods (1974-1976. 1977-1979, etc.). Under the assumption of CRS, they find that average efficiency was lower in the first three periods than in the last three, and that technical efficiency was substantially lower in period 3 (1980-1982) than in any other period.

The authors find that the average scale efficiency (SE) ranged from 0.90 in period 3 to 0.96 in period 6. Based on these results they conclude that the industry is scale efficient. The authors do not, however, test for scale efficiency.[53] Because the authors cannot say with statistical confidence that the mills are scale efficient, it would have been prudent to determine if the average scale efficiency for each period indicated increasing or decreasing returns to scale. The authors found that productivity declined on average by 2.0% per year between 1974 and 1985, but grew at a rate of 3.14% per year between 1985 and 1992. Averaged over the entire period, they estimate productivity grew by 0.82% per year. Also over the entire period, they find efficiency change (i.e., the catching-up effect) grew at 0.47% per year and technical progress (shifting of the efficient frontier) increased by 0.29%.[54]

Although not related to the sawmill industry, Yin (2000) employs both DEA and stochastic frontier analysis (SFA) to analyze the technical efficiency of global producers of bleached softwood kraft pulp (BSKP). The author performs the analyses on a 1996 cross-section of 102 producers. He then compares results obtained with DEA and SFA The author finds that the estimated technical efficiencies based on DEA range from 0.89 to 100 and averaged 0.97. For SFA, all of the technical efficiencies were above 0.99, indicating essentially no variation in relative technical efficiency. Yin conjectures that the lack of variation could be due to the nature of the production process, the data generating process, and the SFA method. He concludes that DEA "could be a better approach in the current context" and that "different methods (of analysis) can cause variations in empirical outcomes."

MEASURING TECHNICAL EFFICIENCY & PRODUCTIVITY GROWTH

The methods introduced by Charnes, Coopers, and Rhodes (1978) (hereafter referred to as "CCR") are used to estimate the aggregate technical efficiency of lumber producers in the Pacific Northwest. These estimates of technical

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[53] The non-parametric test of returns to scale described by Simar and Wilson (2002) was published one year after the Nyrud and Baardsen (2001) article.

[54] Technical change and technical progress are used interchangeably in this study.

efficiency are then used in conjunction with the methods introduced by Färe et al. (1994) to estimate total factor productivity (TFP), technical and efficiency change, and scale efficiency of the lumber producing regions. CCR developed a method to measure the technical efficiency of a *decision making unit* (DMU) relative to the technical efficiency of a set of other DMUs.[55] The linear programming model developed by CCR neither requires the common economic assumptions that the DMUs are either successful profit maximizers, or cost minimizers, nor does it require the imposition of a specific functional form, such as the Cobb-Douglas, CES, or translog. The CCR technique, data envelopment analysis, was inspired by Farrell (1957), which was the first study to put forth the empirical concept of measuring technical efficiency. Farrell showed how information on firms' input and output quantities could be represented in a piecewise manner in order to estimate the industry's production frontier. CCR advanced Farrell's work in several ways. First, they showed that an analysis of technical efficiency posed as a nonlinear programming problem could be converted into a linear programming problem equivalent to Farrell's technical efficiency. CCR also showed the duality of linear programming-derived technical efficiency measures to other, more common economic functions, such as the cost function and Shephard distance function.

Technical Efficiency

Technical efficiency is a measure of a DMU's ability to obtain the maximum amount of output from a given level of inputs.[56] Technical efficiency is

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[55] Note 1: CCR coined the term "*decision making unit*," which includes such otherwise diverse entities as individual firms, aggregates of firms, government agencies, countries, etc.

Note2: The technical efficiency estimates (or "scores") are relative, not absolute, measures of technical efficiency.

[56] This type of technical efficiency is referred to as "output-oriented" technical efficiency. Alternatively, "input-oriented" technical efficiency is a measure of the minimum amount of inputs required to produce a given level of output. Under conditions of constant returns to scale and strong disposability of inputs and outputs, output-oriented and input-oriented technical efficiency are identical.

measured using DEA methods. The reference frontier from which technical efficiency of each DMU is measured is constructed from the subset of DMUs determined to be most technically efficient from the set of all DMUs. As such, the measures of technical efficiency obtained through DEA are relative, not absolute, measures of performance. The measurement of technical efficiency does not require information on prices, costs, or revenue and, therefore, is not a pure economic measure of efficiency.[57]

The reference or “best practices” frontier is constructed from the most technically efficient DMUs in the sample. Figure 9 illustrates a two-dimension efficient frontier in input space (i.e., an isoquant) in which all three DMUs (A, B, and C) produce the same amount of output, but with varying amounts of inputs X1 and X2.

The efficient frontier, L(y), shown in Figure 9: Best Practices Frontier in Input Space is defined by A and B while DMU C is said to operate interior of the frontier because C requires more of each input to produce the same amount of output as either A or B. Because A and B are on the efficient frontier, they are referred to as technically efficient (i.e., technical efficiency = 1.0) and DMU C is technically inefficient (i.e., technical efficiency < 1.0). Point D represents the location on the efficient frontier where a technically efficient *hypothetical* DMU utilizing the same input ratio as C would operate.

The measure of technical efficiency of DMU C is defined by the ratio

$$F_I^C = \frac{(O,D)}{(O,C)}. \tag{1}$$

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[57] Pure measures of economic efficiency would be concerned with minimizing input cost for a given level of output, or maximizing output revenue for a given input set. Economic efficiency can be measured using DEA techniques if input cost and/or output prices are known.

Where F_I^C is the ("Farrell") input-oriented measure of technical efficiency for DMU C.[58]

The underlying assumption is that C could proportionally reduce its input mix and still produce the same amount of output. In principle this reduction could be done by adopting the technology and/or best practices utilized by the technically efficient DMUs. More formally, the input-oriented measure of technical efficiency is defined as

$$F_i(y,x) = \min\{\lambda : \lambda x \in L(y)\}. \tag{2}$$

Where F_i refers to the input-oriented measure of technical efficiency, (y, x) are the vectors of inputs and outputs, respectively, for the i-th DMU, _ is the minimum amount the input bundle can be scaled in order to operate on the efficient frontier, and L(y) is the input requirement set, which contains all combinations of inputs that can be used to produce the output vector y.

The input requirement set used to construct the efficient frontier is constructed as follows:

$$L(y \mid C,S) = \{(x_1, x_2, \ldots, x_N): \tag{3}$$

$$\sum_{k=1}^{K} z_k y_{km} \geq y_m, m = 1,\ldots,M,$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq x_n, n = 1,\ldots,N,$$

$$z_k \geq 0, k = 1,\ldots,K\}.$$

Where C denotes constant returns to scale (CRS),[59] S denotes strong disposability of inputs, x_1, x_2, …, x_n are the input factors, k is the DMU being

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[58] Because of his pioneering work dealing with the empirical measurement of technical efficiency, this measure of technical efficiency is often referred to as *Farrell input-oriented* technical efficiency (as opposed to the *Farrell* output-oriented technical efficiency measure).

considered (k = 1,..., K), M is the number of outputs, N is the number of inputs, and z_k are the intensity variables computed by the model.[60] Implicit in the input requirement set shown in equation 3 are the following regularity conditions (Bates et al. 2004):

1. **Feasibility:** All observed input-output combinations are feasible, $(x_j, y_j) \in L; (j = 1,2,...N)$.

2. **Convexity:** $(x_0, y_0) \in L$ and $(x_1, y_1) \in L \Rightarrow (\lambda x_0 + (1-\lambda)x_1, \lambda y_0 + (1-\lambda)y_1) \in L$, $0 \le \lambda \le 1$.

3. **Free disposability with respect to inputs:** $(x_0, y_0) \in L$ and $x_1 \ge x_0 \Rightarrow (x_1, y_0) \in L$

4. **Free disposability with respect to outputs:** $(x_0, y_0) \in L$ and $y_1 \le y_0 \Rightarrow (x_0, y_1) \in L$

Scale Efficiency

Estimates of technical efficiencies derived under the assumption of a CRS technology are in fact composed of a measure of scale efficiency and a measure of *true* technical efficiency.[61] True technical efficiency is simply technical efficiency estimated under the assumption of VRS. A DMU that is technically efficient relative to a CRS technology is also technically efficient relative to a VRS technology, but the reverse is not necessarily the case. If a DMU is technically efficient relative to a CRS technology it is referred to as scale efficient. For the DMU that is technically efficient relative to a VRS

[59] In this formulation CRS is satisfied. However, technical efficiency could be estimated relative to a variable returns to scale or non-increasing returns to scale technology.

[60] The intensity variables are computed based on the values of both the inputs and outputs of each DMU.

[61] What we estimate as *true* technical efficiency could actually be further decomposed into measures of congestion and *residual* technical efficiency.

technology, but is not technically efficient relative to a CRS technology, the difference is explained by scale inefficiency.

In Figure 10 a VRS production function is represented by the dashed lines connecting points A, B, and C. All three of these points have a technical efficiency of 1.0 under the VRS technology assumption, but only point B is technically efficient under the CRS assumption and is, therefore, also scale efficient.

Because points A and C are technically efficient under the assumption of VRS, they are said to have a true technical efficiency of 1.0, but since they are not technically efficient under the assumption of CRS, they are not scale efficient. Point A is operating at a point of increasing returns to scale (IRS) and point C is operating at a point of decreasing returns to scale. The vertical distance from points A and C to the CRS-based production frontier is the measure of scale inefficiency, respectively, for the two points.

Point D is neither technically efficient nor scale efficient. The output-oriented *true* technical inefficiency for point D is the distance D-D_V.[62] The distance D_V-D_C is the scale inefficiency for point D. The measure of technical inefficiency under the assumption of CRS is composed of the distance D-D_V (true technical inefficiency) plus the distance D_V-D_C (scale inefficiency). Scale efficiency can be determined for a DMU by the ratio of two technical efficiency measures (Färe, Grosskopf, and Logan, 1983).

$$S_E(y,x \mid S) = D_O(y,x \mid C,S) / D_O(y,x \mid V,S) \tag{4}$$

Where

[62] We say "output-oriented" because we hold input use constant and project point D (vertically) onto the VRS frontier. For the "input-oriented" measure of technical inefficiency, we would hold output constant and project point D horizontally onto the VRS frontier. Output-oriented technical efficiency measure is the reciprocal of the input-oriented technical efficiency measure.

$S_E(y,x\,|\,S)$ is the scale efficiency of the input-output set x, y under the assumption of strong disposability of outputs.

$D_O(y,x\,|\,C,S)$ is the output distance function of the input-output set x, y under the assumptions of constant returns to scale and strong disposability of outputs.[63]

$D_O(y,x\,|\,V,S)$ is the output distance function of the input-output set x, y under the assumptions of variable returns to scale and strong disposability of outputs.

If $S_E = 1$, then the DMU is said to be scale efficient. If $S_E < 1$, then the DMU is said to be scale inefficient. S_E does not provide any information as to whether scale inefficiency is due to operating at a point of increasing or decreasing returns to scale. To determine the type of scale efficiency, an additional technical efficiency measure must be derived relative to a non-increasing returns to scale (NIRS) production technology and compared to CRS-based technical efficiency measure.

If $D_O(y,x\,|\,N,S) = D_O(y,x\,|\,C,S)$ then the DMU is operating at a point of increasing returns to scale.[64]

If $D_O(y,x\,|\,N,S) > D_O(y,x\,|\,C,S)$ then the DMU is operating at a point of decreasing returns to scale.

Decomposing efficiency measures into a scale component and a true efficiency component is important because it sheds light on the reason(s) for deviation

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[63] The output distance function is equivalent to the input-oriented Farrell technical efficiency measure.

[64] Where $D_O(y,x\,|\,N,S)$ is the output distance function of the input-output set x, y under the assumptions of NIRS and strong disposability of outputs.

from the efficient frontier. Armed with this information, producers can make adjustments to their production processes to achieve greater levels of productivity.

Productivity Growth

Productivity growth is a measure of the change over time in a DMU's ability to produce output from a fixed level of input.[65] In the simplest case (single input, single output) productivity growth is the change in average product between two periods. In the case of multiple inputs and/or multiple outputs, distance functions are used to aggregate inputs and outputs in order to measure productivity growth. Distance functions allow one to describe a multi-input and/or multi-output production technology without the need to specify a behavioral objective (such as cost minimization or profit maximization) (Coelli, et al., 1998 p222). [66] Distance functions also have attractive mathematical properties, including linear homogeneity, and input and output distance functions are reciprocals.[67]

The measurement of TFP change using DEA methods was introduced by Färe et al. (1994) and is often referred to as the Malmquist productivity index.[68] The Malmquist TFP index measures the change in TFP between two points in time based on the geometric mean of ratios of distance functions.

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[65] Alternatively, productivity growth is a measure of the change over time in a DMU's ability to reduce input use while still producing the same amount of output.

[66] For more information on the distance function, quantity indexes, and productivity indexes see Chambers et al. (1994).

[67] These properties follow from a CRS specification of the distance functions.

[68] The Malmquist productivity index was introduced by Caves, Christensen, and Diewert (1982). The basis of the index dates back to Malmquist (1953) introduction of input quantity index as ratios of distance functions.

$$M_O\left(x^{t+k}, y^{t+k}, x^t, y^t\right) = \left[\frac{D_O^t\left(x^{t+k}, y^{t+k} \mid C, S\right)}{D_O^t\left(x^t, y^t \mid C, S\right)} * \frac{D_O^{t+k}\left(x^{t+k}, y^{t+k} \mid C, S\right)}{D_O^{t+1}\left(x^t, y^t \mid C, S\right)}\right]^{1/2}. \quad (5)$$

Where: $D_O^t\left(x^{t+k}, y^{t+k} \mid C, S\right)$ is the output-oriented distance function based on a representation of technology from time period *t*, input and output quantities from time period *t+k*, and assuming constant returns to scale and strong disposability of inputs. $D_O^t\left(x^t, y^t \mid C, S\right)$ is the output-oriented distance function based on technology from time period *t*, input and output quantities from time period *t*, and assuming constant returns to scale and strong disposability of inputs. The remaining distance function components are similarly defined and allow for intertemporal comparisons of productivity.

The output distance function, D_O, is the reciprocal of the Farrell output-oriented technical efficiency measure, F_O.[69] It is a straightforward matter to use linear programming to estimate the distance function measures necessary to construct the output-oriented Malmquist productivity index.

Following the method described in Färe et al. (1994), all of the distance functions are defined relative to CRS technology, which ensures that the Malmquist index can be interpreted as a measure of TFP. As pointed out by Coelli et al. (1998), among others, the Malmquist index will not correctly measure TFP change (in the sense of changes in ratios of average products as usually defined) when VRS is assumed for the production process.

More recently, Coelli et al. (2005) discuss criticisms of the Färe et al. (1994) assumption of CRS for the distance functions used in the Malmquist TFP index. The main point of criticism deals with the decomposition of the Malmquist TFP index into components of technical change, efficiency change,

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[69] Under the assumption of CRS the output and input distance functions are reciprocals. Likewise the output-oriented and input-oriented Farrell technical efficiency measures are reciprocals. Thus, the distance function measures used in the development of the Malmquist TFP index could be estimated using either the input-oriented or output-oriented Farrell efficiency measures.

and, most importantly, scale efficiency change. The criticism is that if scale efficiency is found to change between time periods t and $t + k$, this reflect a changing VRS technology, not a changing CRS technology. Ray and Desli (1997) propose an alternative decomposition of TFP change that measures technical change relative to a VRS technology and an alternative method for computing scale efficiency change. Coelli et al. (2005) point out that, although the assumption of CRS may impose an internal inconsistency in the calculation of the individual distance functions, the difference in the estimation of TFP between the Färe et al. (1994) approach, which assumes technical change of a CRS technology, and the Ray and Desli (1997) approach, which assumes technical change of a VRS technology, "*…will only be substantive when there are firms within the sample with significantly different scales, and there are scale economies, and there are non-neutral rates of technical change across the different sized firms.*"[70] Grosskopf (2003) points out that the Ray and Desli (1997) overall measure of productivity reduces to the ratio of distance functions evaluated relative to CRS technology. Thus, it remains the case that to ensure TFP is measured correctly (as a ration of output to input), equation 5 must be evaluated relative to a CRS technology.

For the i-th DMU, a total of four distance functions must be specified and estimated to compute the Malmquist TFP index between period t and t+k. For a sample of n DMUs over T-time periods, a total of $n*(T\text{-}2)$ distance function must be computed. Thus, as the number of DMUs and/or time periods gets large, the number of LPs that must be specified and estimated gets very large.

Efficiency change is a measure of the change in the relative distance of a DMU from the efficient frontier. For the case where a DMU operated closer to the efficient in time period t+k than it did in time period t, efficiency change is positive. Efficiency change is often referred to as the "catching up" effect and is computed as:

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[70] In addition, Coelli et al. (2005) state that within DEA, the VRS approach can result in infeasibilities in some inter-period distance function calculations.

$$EfficiencyChange = \frac{D_O^{t+k}\left(x^{t+k}, y^{t+k} \mid C,S\right)}{D_O^{t}\left(x^{t}, y^{t} \mid C,S\right)}. \quad (6)$$

Again, the distance functions are reciprocals of the Farrell output-oriented technical efficiency measure and are estimated using DEA.

The other component of productivity change, technical change, is a measure of shifts in the production frontier. As such, it can be thought of as a measure of how much impact a DMU had in shifting out the efficient frontier of all DMUs. Technical change is computed as:

$$TechnicalChange = \left[\frac{D_I^{t}\left(x^{t+k}, y^{t+k} \mid C,S\right)}{D_I^{t+k}\left(x^{t+k}, y^{t+k} \mid C,S\right)} * \frac{D_I^{t}\left(x^{t}, y^{t} \mid C,S\right)}{D_I^{t+k}\left(x^{t}, y^{t} \mid C,S\right)}\right]^{1/2}. \quad (7)$$

As in the calculation of the Malmquist productivity measure, this component of productivity is derived through the calculation of the reciprocals of the distance functions (Farrell technical efficiency) as the solutions to DEA type linear programming problems. Technical change is the geometric mean of the technology shift between periods t and $t + k$, evaluated at $\left(x^{t}, y^{t}\right)$ and $\left(x^{t+k}, y^{t+k}\right)$.

BOOTSTRAPPING IN NON-PARAMETRIC FRONTIER MODELS

Perhaps the most obvious shortcoming of the empirical DEA literature is the lack of statistical testing and inference. Implicit in virtually all of the published studies that employ DEA is either the assumption that DEA methods are non-statistical or the statistical properties are unknown and cannot be approximated. Regardless of the assumption, the result is that the empirical literature is comprised of only a few recent studies that attempt to make confidence statements on the efficiency measures of interest. The vast majority of the literature provides only point estimates of efficiency measures and statements by the author(s) regarding the strength of the results are purely conjecture. Based on recent research by Simar and Wilson (1998, 1999, 2000, 2002), statistical inference and hypothesis testing are now possible with DEA.

Simar and Wilson (2000) describe a method for determining the statistical properties of the DEA technical efficiency estimators. The method the authors propose allows for the construction of confidence intervals on the true technical efficiency, as well as a method for estimating potential bias of the technical efficiency estimates. DEA is a frontier-based estimation method, thus only the most technically efficient DMUs are used to construct the efficient frontier. Because the frontier from which the technical efficiency of each DMU is measured is constructed from a finite sample of DMUs, the technical efficiency estimates are sensitive to the sampling variations of the empirical frontier (Simar and Wilson, 1998). Bias in the estimation of technical efficiency occurs when the empirical frontier is not equivalent to the actual, but unobserved frontier. The bootstrapping method proposed by Simar and Wilson (2000) allows one to estimate the extent of this bias.

$$bias_{\hat{\tilde{N}},k} = E_{\hat{P}}\left(\hat{\theta}_k^*\right) - \hat{\theta}_k$$

Where $\hat{P}$ represents the estimate of the data generating process (DGP) based on the known bootstrap distributions, $\hat{\theta}_k$ is the measurement of technical efficiency based on the empirically estimated frontier (and unknown DGP), and $\hat{\theta}_k^*$ is the measurement of technical efficiency for the k-th DMU based on the known bootstrap distribution. Please refer to Simar and Wilson (1998) for detailed information on how to estimate the bias of $\hat{\theta}_k$.

The bootstrap method is used to approximate the DGP of the underlying distribution of technical efficiency scores. From the bootstrap distribution, measures of bias can be estimated for technical efficiency.[71] The naïve bootstrap approach of constructing pseudo samples by re-sampling from the empirical distribution of input-output combinations does not adequately approximate the DGP (Simar and Wilson, 2002).[72] Rather, the smooth bootstrap approach described by Simar and Wilson (1998, 2000b) must be used. The problem with the naïve bootstrap is quite simple. The density function, *F*, of the process that generates the inefficiency scores, θ, is by definition continuous on the interval (0-1]. The empirical density function, $\hat{F}$, however contains positive mass at $\hat{\theta} = 1$. i.e., the empirical density function includes at least one (and likely more than one) DMU that is perfectly technically efficient. Thus, for DMUs at or very near the upper bound (1.0), $\hat{\theta}$ is a biased estimator of θ.

The approach outlined by Simar and Wilson (1998, 2000b) improves the estimation of *F* by smoothing the empirical density function $\hat{F}$ and then using the reflection method described by Silverman (1986) to overcome the boundary condition that $\theta < 1$.[73] Following this same bootstrapping methodology, confidence intervals can be derived for Malmquist productivity indices (Simar and Wilson, 1999) and for tests of returns to scale (Simar and Wilson, 2002).

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[71] In addition, confidence intervals for measures of technical efficiency and Malmquist productivity growth indices can be constructed and critical values for testing hypothesis on returns to scale can be derived.

[72] The problem with the naïve bootstrap is that it put equal probability (1/n) on each input-output combination in the sample.

[73] That is, the true (unobserved) technical efficiency scores will be less than unity. The reflection method transforms ("reflects") each empirical efficiency score, $\hat{\theta}_i \leq 1$ by its symmetric image $2 - \hat{\theta}_i \geq 1$ and then estimates the kernel density from the resulting 2n set of scores (see Simar and Wilson 1998 p55).

THE DATA

This analysis assumes that the production of lumber is a function of four inputs: sawlogs, labor, capital, and *"other" inputs*. These variables are discussed in greater detail below and descriptive statistics are provided in Table 16. Mill-level data on lumber production, sawlog consumption, and milling capacity were obtained for Washington sawmills from The Washington Department of Natural Resources (WDNR). The WDNR collects these data through its biennial mill survey. Data for 1968 through 2002 (a total of 18 time points) are used in this analysis. County (or multi-county) level employment data for SIC 242 were obtained from the Washington Employment Security Department. Washington was segmented into five regions: westside (Regions 1 and 2), north central (Region 3), south central (Region 4), and the Inland Empire (Region 5). The regions are shown in Figure 11.[74]

Mill surveys similar to those for Washington State were also conducted for Oregon sawmills, however, neither mill-level data were available, nor were mill surveys conducted as often as they were in Washington. Survey data were obtained for Oregon for 1968, 1972, 1976, 1982, 1985, 1988, 1992, 1994, and 1998. Data from the surveys were published at the county or multi-county level by the Pacific Northwest Forest and Range Experimental Station.[75] From these data, four regions were configured (see Figure 11). The Oregon mill surveys provide information on the lumber-producing capacity, the volume of sawlogs processed, and the amount of lumber produced per county/county group. Data on SIC 242 employment by county/county group were obtained from the Oregon Employment Department for all relevant years.

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[74] See Chapter 3 for more information on the data for Washington and Oregon used in this analysis.

[75] Because the number of sawmills in Oregon decreased substantially between 1970 and 1998, county groups have become consistently larger and fewer.

Output and Input Variables

Lumber is the total volume in million board feet (MMBF) lumber tally of hardwood and softwood lumber produced by the mills of each region.

Capital is a measure of the maximum service flow represented by the total installed lumber producing capacity in thousand board feet (MBF) per 8-hour work shift.

Labor is the total man hours worked by each region's SIC 242 employees during the year. Labor is calculated as *Labor = Total SIC 242 Employment * Average Operating Days*[76] * *Average Number of Eight-hour Work Shifts*[77] * *8 Hour shift*.

Sawlogs is the total volume in MMBF log scale of hardwood and softwood sawlogs utilized by the region's mills.[78]

Other Inputs is an estimate of the cost of energy and operations and maintenance supplies used in the manufacture of lumber deflated to 1970 dollars. These costs were not measured in either the Washington or Oregon mill surveys and could not be directly obtained from other sources. They were approximated for each region by developing an index of the average quantity of energy and supplies used in the manufacture of lumber.[79] The index was

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[76] Average Operating Days is calculated from mill-level data and was weighted based on each mill's lumber production.

[77] Average Number of Eight-hour Shifts is also calculated from mill-level data and was weighted based on each mill's lumber production.

[78] For westside mills, log volumes are measured on a 32-foot Scribner basis, whereas eastside mills measure logs based on a 16-foot Scribner basis. The reason for the difference is due the typical log lengths produced from westside and eastside forests. It is assumed in this analysis that the different scaling bases are incorporated into the production function of each mill and are a function of estimated lumber recovery.

[79] A separate index was developed for Oregon and Washington and for westside and eastside mills (a total of four indexes), based on historical input price data published by Resource Information Systems, Inc. (RISI). The indices were created by deflating the current year cost of energy and supplies required to produce one MBF of lumber. Energy costs were deflated based on *Industrial Sector Energy Prices* obtained from the Energy Information Administration.

multiplied by the lumber output of each DMU in corresponding years, resulting in a quantity-like measure of energy and operation and maintenance supplies usage ("other inputs").

The Full Cumulative (FC) DEA Method

As discussed above, the data set is an unbalanced panel consisting of only nine DMUs, five of which are observed on a biennial basis (Washington regions) and four of which are observed periodically over the analysis period (Oregon regions). For any year within the panel, there are data on as few as four DMUs (in 1985) and for all other years there are data on either five or nine DMUs. To estimate productivity growth (as well as technical and efficiency change) between points in time using DEA methods, one must construct the empirical production frontier for each point in time. Four or five data points provide far too few degrees of freedom when the production process is theorized to consist of four inputs and one output (i.e., five dimensions). Banker et al. (1989) proposes a rule that the number of observations used to project the efficient frontier should be equal to or greater than $3(m + s)$, where m is the number of inputs and s is the number of outputs. This rule suggests that for our 5-dimension problem, a minimum of 15 observations are required for each cross-section.

Nghiem and Coelli (2002) faced a similar problem in their analysis of productivity change in Vietnamese rice production. The authors used aggregated data for eight agricultural regions and hypothesized a production process that required five inputs to produce one output (rice). They proposed two methods to alleviate the degrees of freedom problem. The first was a moving average approach, which entailed constructing overlapping windows of data, where the size of each window was equal to size S. For their study the

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Operation and maintenance supply costs were deflated by the Producer Price Index for *Intermediate Materials: Supplies and Components*.

authors arbitrarily chose S to equal three periods. Thus, the first window included data for periods 1, 2, and 3. The second included periods 2, 3, and 4; and so on. Each window of data would then be used to construct a production frontier and from these the distance functions necessary to calculate the Malmquist indices.

The second method proposed by Nghiem and Coelli, andthe one adopted for this analysis, is referred to as the *Full Cumulative* (FC) *DEA Method.* It also entails constructing overlapping windows of data, but instead of an arbitrarily sized window (e.g. three periods) each window retains all of the data from the previous window plus the current year's data. Thus, for period 1 the production frontier would be constructed from the most technically efficient DMUs observed in period 1, for period 2 the production frontier would be constructed from the most technically efficient DMUs observed in periods 1 and 2, and so on. For the final period, the production frontier would be constructed from the most technically efficient DMUs observed at any time during the analysis period. Each period's production frontier is, therefore, constructed from the cumulative experience of the current period and all previous periods. This formulation implicitly assumes that technical progress cannot be negative—not an extreme assumption. That is, the production frontier can either be static between time periods t and $t+1$ or can shift outward, but it cannot shift inward. The FC formulation does not affect efficiency change in the same way. Thus, the position of a DMU relative to the production frontier can increase, decrease, or remain unchanged. As a result, productivity can also increase, decrease, or remain unchanged.

EMPIRICAL RESULTS

Figure 12 shows the weighted average and minimum and maximum technical efficiency scores for each year of the analysis. The weighted average and range of the data represented in Figure 12 are based only on the actual data for each year, but, as discussed above, the FC method was used to create the efficient frontier for each year.[80] It is interesting to note that for a number of years (1970, 1974, 1978, 1980, 1986, 1990, and 2000) the maximum technical efficiency score is less than unity. This implies that the most technically efficient DMU in that year was not as technically efficient as one or more DMUs from earlier years. Figure 12 also shows that the minimum technical efficiency score decreases over time. Decreases in the minimum technical efficiency imply that the least efficient regions are increasingly falling behind the most efficient regions. The regions that are found to be falling behind are consistently north central and south central Washington and eastern Oregon (regions 3, 4, and 9). The weighted average of the technical efficiency estimates is much nearer the top of the range, indicating that it is one or more of the smaller regions setting the lower range. This implies that it is the smaller regions that are falling behind the larger regions in technical efficiency and, more importantly, productivity.

Appendix Tables A1 – A9 show the technical efficiency and bias-adjusted technical efficiency estimates for each region for each year of the analysis. The tables also show the upper and lower bounds of the 95% confidence interval on the true technical efficiency measure. These results are shown for both the CRS and VRS models. The bias-adjusted measure of technical efficiency is derived by subtracting the bias estimate from the technical efficiency estimate. VRS is a much less restrictive assumption than CRS, therefore, the estimates of technical efficiencies under VRS are at least as great as those estimated under CRS. For most regions the difference between the VRS and CRS technical efficiency estimates is not great, but for north-central and south-central Washington the difference is substantial.

For the eight years in which data were collected for both Oregon and Washington, regions 6, 7, and 8 consistently posted the highest technical

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[80] Thus, Figure 12 represents the current-year subset of the FC data set.

efficiency scores. All of these regions are located in western Oregon, which has historically had the highest concentration of lumber producers and lumber production in the Northwest. This preeminence in lumber production has faded to some extent since the late 1980s, but western Oregon lumber producers still produce approximately as much lumber as all other regions combined. Based on the estimates of technical efficiency, it appears that western Oregon lumber producers remain the industry leaders in terms of technical efficiency.

Table 17 presents the results of the analysis of scale efficiency. Scale efficiency was calculated for those years in which data were collected on all nine regions and for 2002 for the Washington regions. The *Frontier Efficiency Analysis with R* (FEAR) software (Wilson, 2005) was used to compute critical values used to test the hypothesis of CRS.[81] For the four Oregon regions, the null hypothesis of CRS could not be rejected for any year. For the five Washington regions, returns to scale varied year by year. The two western Washington regions (regions 1 and 2), generally operated at a point of CRS, but Region 1 operated at points of IRS in some earlier years and Region 2 operated at a point of DRS in 1976 and 1998.

In aggregate, Region 3 producers operated at a point of IRS in all periods and Region 4 producers operated at a point of IRS in 1972, 1992, 1994, 1998, and 2002. Regions 3 and 4 are the two smallest regions in terms of lumber production and sawlog supply. Regions 5 and 9 are also relatively small, but, in aggregate, producers were scale efficient over the past two decades. The difference in scale efficiency between regions 5 and 9 and regions 3 and 4 may be due to environmental characteristics of the regions, as well as differences in the willingness and ability of mill owners and managers to make adjustments toward scale efficiency.

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[81] Following the procedure described in Simar and Wilson (2002), the null hypothesis of CRS is rejected if $\hat{S}_E$, the estimate of scale efficiency is less than the critical value (alpha = 0.01).

Productivity growth, technical progress, and efficiency change were estimated using the Malmquist-type productivity indices. Growth rates were estimated for the following three periods:

- Period 1: 1968-1982[82]
- Period 2: 1982-1992[83]
- Period 3: 1992-2002[84]

For each period, the starting and ending year corresponds to a year in which mill surveys were conducted for both Oregon and Washington—with one exception. As discussed above, 1998 was the last year in which survey data were obtained for Oregon.[85] For Period 3, therefore, the average annual TFP growth and technical and efficiency change for the Oregon regions is based on 1992 and 1998 data. Table 18, Table 19, and Table 20 show the average annual percent changes in the respective productivity measure for each region for each period.[86] Following the methods developed in Simar and Wilson (1999), the FEAR software was used to construct the upper and lower bounds of the 95% confidence intervals for the true value of each of the productivity measures.

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[82] During this period, the U.S. experienced strong housing demand. Harvest levels on federal lands were high and the average diameter of sawlogs was relatively large. Inflation grew substantially over this period, which ended in a major recession.

[83] Housing demand was relatively low during this period. Public cut was high except after 1990 and average log size declined gradually over the period. Inflation also declined throughout the 1980s, but the period ended in a minor recession.

[84] During this period the U.S. experienced steady housing growth and low inflation. Log supply contracted substantially as harvests on federal lands declined precipitously.

[85] The mill survey was conducted in Oregon in 2002-2003. I was not able to obtain these data for the analysis.

[86] Average annual (compound) growth rates were computed using the formula $\ln(I_t - I_{t-n})/n$, where I_t and I_{t-n} are the index values in time t and $t + n$, respectively, and n is the number of years.

For the PNW as a whole, productivity growth increased by approximately 0.5% per year during Period 1 (1968 - 1982), but growth between the nine regions varied greatly. The regions that experienced the greatest growth were all in Washington and included both westside regions and the north central region. On the other extreme, Region 9 (Central and Eastern Oregon) actually declined in productivity during Period 1. Sawmill productivity grew by almost 1.0% per year in Washington as a whole, but was not statistically different from zero in Oregon. Productivity growth was decomposed into technical and efficiency change. Mills in both states experienced technical progress during Period 1, with technical progress increasing on average by 0.75% per year for Washington sawmills and the average technical progress of Oregon mills increasing by 0.52% per year.

The two states differed considerably with respect to efficiency change. While efficiency change for Washington sawmills was not statistically significantly different from zero, Oregon mills actually experienced negative efficiency change (-0.33% per year). Thus, even as Oregon's sawmilling industry experienced technical progress between 1968 and 1982, the industry ended the period further from the technical frontier than it started. Because of this, there was no discernable growth in productivity for the period.

Oregon's sawmill industry fared better during Period 2 (1982-1992), experiencing an average annual rate of productivity growth of 0.47% (see Table 19). Technical change was positive and very similar to the rate of technical progress experienced in Period 1. Productivity growth for Washington's sawmill industry was a little stronger than Oregon (0.54%), but only half the rate experienced during Period 1. Like Oregon, Washington experienced positive technical progress and essentially no efficiency change. Productivity change varied between the regions, with Washington's Region 1 experiencing the greatest rate of growth (1.03%) and Washington's Region 3 and Oregon's Region 9 experiencing negative growth.

Productivity growth among the regions showed the greatest variability in Period 3 (1992-2002), with Oregon's regions 7 and 9 experiencing the greatest rate of productivity growth at 2.16% and 1.87%, respectively (see Table 20).[87] Conversely, Washington's Region 4 and Oregon's Region 6 experienced negative productivity growth of -0.70% and -0.30%, respectively. For the PNW as a whole, productivity increased by a little more than 1.0% per year, with Washington's mills outpacing Oregon's mill by a small margin. Technical change was positive and strong for all regions and efficiency change varied substantially across region, with some regions experiencing positive efficiency change and other regions experiencing no efficiency change or negative change.

Which regions were the leaders in productivity growth and technical change? None of the nine regions consistently posted the highest rate of productivity growth or technical change during all three periods. Nevertheless, when considering average annual growth over the 30 years of data, four regions stand out. Regions 1 and 2 (western Washington), Region 5 (Inland Empire), and Region 7 (in northwest Oregon) experienced the highest average annual rates of productivity growth at 1.1%, 1.0%, 0.9%, and 2.8%, respectively. Most of the productivity growth experienced by these four regions was attributable to technical change and, not coincidentally, none of these regions experienced negative efficiency change.

There are only two comparable analyses that examine productivity growth in the sawmill industry using DEA. In their analysis of the Norwegian sawmill industry, Nyrud and Baardsen (2002) estimated that over the period 1974-1991 productivity growth, technical progress, and efficiency change increased on an average annual basis by 0.82%, 0.29%, and 0.47%, respectively (See Table 21). Comparatively, productivity growth in the PNW over the period

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[87] Please note, Oregon data only extends through 1998. Average annual growth rates for Oregon regions are based on this 6-year period, whereas annual growth rate for Washington regions are based on entire 10-year period.

1974-1992 is estimated to have increased by 0.78% per year and the upper bound on the 95% CI for the true growth rate is 0.92%, thus encompassing the productivity growth rate for the Norwegian sawmill industry. With respect to technical and efficiency change, the estimates for Norway are much different from those derived for the PNW. This difference is not unexpected. Direct comparison between the Nyrud and Baardsen analysis and this analysis is complicated by three factors: (1) the substantial environmental differences between Norway and the U.S. PNW, (2) the fact that Nyrud and Baardsen analyze mill-level data, whereas aggregated data are analyzed in this study, and (3) Nyrud and Baardsen model a 6-input, 3-output production process, whereas a 4-input, 1-output production process is modeled in this analysis.

Using a sub-set of the data employed in this analysis, Helvoigt and Grosskopf (2005) estimated that productivity in the Washington State sawmill industry increased by almost 1.0% per year between the early 1970s and late 1990s (see Table 21). They found that technical change was strongly positive (1.11%), but efficiency change was small and negative (-0.14%). The authors did not perform the bootstrap procedure on the Malmquist indices suggested by Simar and Wilson (1999) so confidence intervals on the true index values were not estimated. It should also be noted that Helvoigt and Grosskopf (2005) formulate a 3-input production process consisting of sawlogs, labor, and capital. This formulation differs from the current study, which in addition to these three inputs includes the *other* variable.

Comparison to Results from Stochastic Frontier Analysis

Employing the same data relied upon in this analysis, Chapter 3 specifies and estimates a stochastic frontier production function (SFPF). Of relevance to the current analysis are the estimates of technical efficiency, productivity growth, technical and efficiency change, and returns to scale. Like DEA, stochastic frontier analysis (SFA)[88] allows one to estimate the production frontier for a group of DMUs, based on the performance of the most technically efficient members, and to obtain productivity related measurements. However, the two methods differ in many ways. First, SFA is an econometric-based technique, providing standard error estimates and allowing for hypothesis testing. SFA also allows for the direct estimation of panel data models. This is a substantial advantage over DEA, which requires the construction of a production frontier for each period of data. Measures such as output elasticities and elasticities between inputs are also easily estimated through the regression-based approach.

The econometric-based SFA technique also has disadvantages relative to DEA. SFA requires the imposition of a (potentially incorrect) functional form, thus opening the door to possible model misspecification. Relying on a flexible functional form, such as the translog, can reduce or eliminate this potential problem, however, this flexibility often comes at the cost of failing one or more of the regularity conditions. Sauer and Hockman (2005) review eight recently published empirical studies that estimate a stochastic production function. They find that whereas many of the analyses meet the regularity condition of monotonicity for each input, all of the analyses fail the regularity condition of diminishing marginal productivity for at least one input, and all of the analyses fail the regularity condition of quasi-concavity.[89] Failure to meet the regularity conditions for a production function may lead to efficiency-related estimates that are not theoretically consistent. By not requiring a functional form *a priori*, DEA avoids the complexity of testing for, and possibly imposing, regularity conditions required by SFA methods. By comparison, regularity conditions (as is discussed above) are incorporated directly into DEA model. And these conditions are incorporated globally. For the SFA model developed

[88] The stochastic frontier production function (SFPF) is a subset of SFA.

[89] See Chapter 3 for more information on the regularity conditions for a production function.

in Chapter 3, regularity conditions were examined and shown to hold only at the mean value of the data.

Technical Efficiency Comparison

As Figure 13: Scatter Plot of SFPF and DEA Technical Efficiency Estimates (each point is a DMU for a Specific Year) shows, there appears to be a weak relationship between the technical efficiency estimates derived from the DEA and SFPF approaches. The correlation coefficient between the two sets of efficiency scores is 0.17, a further indication of their weak linear relationship. Nevertheless, over the entire study period (1968-2002), the average technical efficiency estimate for the SFPF and DEA approaches were almost identical at 97.6% and 97.2%, respectively.[90] In his analysis of bleached softwood kraft pulp producers (BSKP), Yin (2000) found that all of the technical efficiency estimates derived from his SFPF model were greater than 99.0%. Based on these results, he did not bother with a comparison to his DEA results. He conjectures that the consistently high scores could have been caused by: "the production process, the data generating mechanism, and the SFA (*SFPF*) procedure."

A phenomenon similar to that described by Yin (2000) could be observed with the SFPF estimated in Chapter 3. The estimated technical efficiencies for the first half of the analysis period (1968 - mid-1980s) were consistently above 98.0% and most were above 99.0%. Over the latter half of the analysis period the technical efficiency estimates showed much greater variability with scores ranging from 89.5% - 99.5%.

The differences in the technical efficiency scores obtained through SFPF and DEA in this analysis and Chapter 3 are likely explained by differences in the two techniques and by the relatively small sample size used in the two

[90] Comparatively, the average technical efficiency estimates derived using DEA under the assumption of CRS was 93.4% and the variance on the estimates was substantially greater than SFPF or DEA-VRS.

analyses. Unlike DEA, stochastic frontier analysis does not assume that all deviation from the efficient frontier is due to technical inefficiency. Rather, deviations from the frontier are assumed to be composed of a (one-sided) inefficiency error and a (symmetric) random disturbance. Using maximum likelihood methods, the SFPF model decomposes the total error into the two parts. As discussed in Chapter 3, very high estimates of technical efficiency (greater than 0.98) were derived for all DMUs for the first half of the analysis period (through 1984). It is likely that, for the SFPF model estimated in Chapter 3, the vast majority of the error for the first half of the analysis period was projected to be random disturbance and not inefficiency.

In the DEA analysis the production frontier is re-estimated for each year (or period) of data. This is not the case with SFPF. Rather, all of the data are used to estimate the parametric function from which technical efficiency for each DMU for each year is estimated. DEA is a deterministic procedure and, by definition at least one—and generally more than one—DMU will form the efficient frontier and will, therefore, have a technical efficiency of 1.0. This is not the case with the SFPF. As the name implies, the SFPF estimates a "stochastic" frontier from which the technical efficiency of each DMU is measured. Although many DMUs may be found to lie very close to the efficient frontier, no DMUs lie exactly on the frontier.[91] Further, as Figure 13 indicates, for many DMUs, what DEA assumes to be inefficiency, the SFPF found to be (symmetric) random noise.

Which method produces the most reliable estimates of technical efficiency? It is difficult to discern. According to the SFPF model, all DMUs were essentially technically efficient from 1968–1984.[92] In other words, according to the SFPF results, essentially all of the deviation between the DMUs and the efficient frontier over this period was due to random noise. Comparatively, the DEA

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[91] That is, there is no positive mass at the value 1.0.

[92] I.e., the estimated technical efficiencies of all DMUs were greater than 0.98.

results indicate that technical efficiency ranged from 0.89 to 1.0 during the period 1968-1984. Does this greater level of variation in the DEA-based estimates represent actual variation in the technical efficiency of the DMUs or is DEA confusing technical *in*efficiency with random noise?

Returns to Scale Comparison

Returns to scale (RTS) is estimated from the SFPF coefficient estimates in the same manner as a traditional production function.[93] Although RTS is estimated much differently in DEA, the measure can be compared across estimation methods. In Chapter 3, RTS was estimated for the entire PNW, not for individual regions. RTS was estimated for three individual periods: the 1970s, 1980s, and 1990s, as well as for the entire study period (the "long run"). Because the SFPF method requires the estimation of only one production frontier, which can account for shifts in the frontier over time and changes in the position of DMUs relative to the frontier, it was not necessary to estimate RTS for individual years. Thus, though the econometrically-derived and LP-derived estimates of RTS are theoretically comparable, the RTS estimates for Chapter 3 and this study are not *exactly* comparable. Nevertheless, they were derived using the same set of data and one should expect *a priori* that they would not be contradictory.

Table 22 shows the RTS results for the two studies. For Chapter 3, CRS could not be rejected for any period of the analysis, though the point estimate of RTS has increased over time indicating that the sawmill industry of the PNW has moved from a point of slightly decreasing RTS scale to points of slightly increasing RTS. Nevertheless, the results of Chapter 3 indicate that RTS was

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[93] In Chapter 3, the author estimated the SFPF using a translog functional form, therefore, returns to scale for a 4-input production function is estimated by $\sum_{i=1}^{4} \frac{\partial \ln y}{\partial \ln x_i}$.

not statistically significantly different from CRS over the study period. The results from this study also indicate that most regions operated at a point of CRS throughout the study period, though the results suggest that some regions operated at a point of IRS in certain years and Region 2 operated at a point of DRS in 1976 and 1998. The DEA results also indicate that the four Oregon regions were scale efficient throughout the study period.

Productivity Growth and Technical and Efficiency Change Comparison

Unlike DEA, where productivity growth is measured by the ratio of distance functions, in SFA productivity growth is measured as the sum of technical progress, efficiency change, and changes in scale efficiency. In SFA, technical progress is measured from time variable(s) within the production function,[94] efficiency change is measured as the ratio of technical efficiency estimates,[95] and changes in scale efficiency are measured from estimates of RTS derived from the production function coefficients. Although productivity is measured differently in DEA and SFA, the two methods are intended to measure the same phenomenon and, therefore, are comparable.

Table 23 provides a comparison of the estimates of productivity growth and technical and efficiency change estimated in this analysis and in Chapter 3. For each period of comparison, the SFA-derived estimates of productivity growth are greater than those derived through DEA. For the 1970s the average annual estimate of productivity growth from the SFPF is 3-times

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[94] In Chapter 3, time enters the translog production function in linear and quadratic form, as well as through interaction with the four inputs.

[95] The measures of technical efficiency estimated from the stochastic production function are computed as the ratio of the observed output for the *i*-th DMU relative to that DMU's potential output (defined by the estimated production frontier). These measures of technical efficiency are output-oriented "Farrell-type" measures of technical efficiency. The computation of efficiency change from a SFPF is analogous to the computation in DEA.

greater than the DEA estimate. The SFPF estimate of productivity growth climbs to 4-times the DEA estimate in the 1980s, and then drops to 2-time the DEA rate in the 1990s.

The estimates of efficiency change from the two studies match somewhat more closely. The SFPF estimates for the 1970s and 1990s fall within the DEA-based confidence intervals and fall only slightly outside of the DEA confidence interval for the 1980s. The results of the two methods differ greatly, however, with respect to technical progress. It is the substantial difference in the estimates of technical progress that is responsible for the sizeable difference in the estimates of productivity change. For each of the three periods, the SFPF-based estimates of productivity growth increase on an average annual basis by 1.6% to 2.1%. The DEA-based estimates of technical progress never exceed 1.2% average annual growth.

Do the DEA and SFPF results support or contradict each other? The substantial difference in the estimates of technical progress and productivity growth between the two methods should certainly be of concern especially for those instances where the confidence intervals derived from the two methods do not overlap. Why the sizeable difference in technical and productivity change when the same data were used to in both analyses? The answer may be related to the functional form imposed on the SFPF model. The translog, although a flexible functional form, imposes more structure than do DEA models. The SFPS model consists of 25 variables in the production function (8 of which are regional dummies) and the simultaneously estimated inefficiency effects equation has three variables. With 126 observations, degrees of freedom should not be of too great of concern. However, there are at most only 9 observations in any one cross-section and this may have affected the model's ability to construct and evolve the production frontier.

Although the rate of technical progress differs substantially between the two methods of analysis, it is important to note that the estimates of efficiency change are very similar and the direction of change of all the measures is consistent.

DISCUSSION

In this study, the performance of the NW sawmill industry was examined over a 3-decade period using DEA techniques. On a period-by-period basis the relative technical efficiency of each sawmilling region was estimated and it was found that the range of the technical efficiency scores increased over time. The increase in the range of scores was due to decreases in the minimum technical efficiency, as the maximum score (given the nature of DEA) was consistently at or near 1.0. Over the study period, the (weighted) average technical efficiency of the NW sawmill industry remained roughly constant or even increased slightly (even as the minimum scores declined), indicating that it was the smaller regions that were at or near the minimum of the range of technical efficiency scores.

Estimates of technical efficiency are based on a point in time and are not comparable across time. This is because technical efficiency is measured relative to the efficient frontier and the frontier shifts over time. In order to compare performance over time, productivity change, technical progress, and efficiency change were examined using the Malmquist productivity indices. Average productivity of the Northwest sawmill industry was found to have grown by approximately 0.65% per year. Productivity growth was decomposed into technical and efficiency change. Technical progress (i.e., shifting out of the efficient frontier) increased on an average annual basis by 0.76% and efficiency change (i.e., movement of the average DMU toward the efficient frontier) was negative (-0.11% per year on average). While technical progress pushed out the efficient frontier of the NW sawmilling industry, it did not affect all regions equally. Because some regions experienced less technical progress than others, they actually moved further away from the (shifting) efficient frontier.

The bootstrap method developed by Simar and Wilson (1998, 1999, 2000a, 2000b, 2002) is applied in order to construct confidence intervals and perform hypothesis testing. This study is the first to extend the Simar and Wilson bootstrap technique to an examination of technical efficiency in the forest products industry. The lack of hypothesis testing and statistical examination has long been recognized as the major shortcoming of the DEA method. This study is a part of the small, but growing body of empirical DEA literature that includes statistical analysis. It is the author's opinion that future studies of the forest products industry that utilize DEA methods should also incorporate statistical analysis based on or similar to the Simar and Wilson bootstrap technique. Incorporating the bootstrap techniques into this analysis allowed for hypothesis testing of estimates of scale efficiency, as well as the construction of confidence intervals for the technical efficiency and productivity change estimates, thus providing a means of placing statistical confidence on these otherwise non-parametric calculations.

The final purpose of this study was to compare the DEA-based results with those obtained in Chapter 3 using SFPF. While there is a small but growing literature devoted to comparative analysis of the SFA and DEA techniques, there are very few studies that compare the two techniques with respect to productivity growth and its components. Yin (2000) relies on SFA and DEA to examine data on a cross-section of pulp producers. Murillo-Zamorano and Vega-Cervera (2000) compare the results from a Cobb-Douglas SFPF and DEA in their examination of a cross-section of 70 U.S. electric utilities. The authors of each of these studies discuss the relative merits of the two approaches and conclude that their results encourage continued collaboration between DEA and SFA. Based on the results of this analysis, the collaborative use of DEA and SFA is arguably even more important when working with panel data as a means to corroborate, contradict, or improve upon the results derived through either method.

In comparing the results of this study with those from Chapter 3, it was found that the DEA-based estimates of technical efficiency neither corroborate nor contradict the SFPF-based estimate of technical efficiency. Rather, the two techniques provide alternative estimates of technical efficiency. With respect to RTS, DEA corroborates the results obtained through SFPF and, perhaps, improve upon those results by providing region-level estimates. With respect to efficiency change, DEA clearly corroborates the results obtained through SFPF. For productivity growth and technical progress, the DEA estimates are substantially lower than those obtained through SFPF. This is an important finding and one that should lead to caution when relying on the results derived from only one of the two methods. It is unclear why productivity growth and technical progress estimates differed so substantially between the two methods

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Figure 12: DEA-based Technical Efficiency Estimates Assuming CRS Production Function

Figure 13: Scatter Plot of SFPF and DEA Technical Efficiency Estimates

Table 16: Descriptive Statistics for Output and Input Variables (per region)

Variable	Mean	St. Dev.	Median	Min	Max
Lumber Production (MBF lumber tally, softwood + hardwood)	1,020,347	945,315	527,840	136,030	3,706,856
Sawlogs (MBF Log Scale)	694,017	635,217	361,980	89,957	2,683,044
8-Hour Capacity (MBF Lumber Tally)	3,152	2,876	1,760	365	11,675
Labor (Thousands of Total Person Hours)	12,966	13,336	7,148	1,148	57,510
Other (Energy & Supply Costs in Thousands of 1970 Dollars)	7,515	6,829	4,268	893	28,020

Table 17: Scale Efficiency Estimates and Critical Values for Testing Null Hypothesis of Constant Returns to Scale

Year	Region								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1968	0.931 (0.973) **IRS**	1.000 (0.960) CRS	0.907 (0.926) **IRS**	0.936 (0.914) CRS	0.899 (0.925) **IRS**	1.000 (0.919) CRS	1.000 (0.941) CRS	1.000 (0.896) CRS	1.000 (0.884) CRS
1972	0.949 (0.979) **IRS**	1.000 (0.970) CRS	0.912 (0.971) **IRS**	0.916 (0.948) **IRS**	0.928 (0.972) **IRS**	1.000 (0.961) CRS	1.000 (0.968) CRS	1.000 (0.929) CRS	1.000 (0.929) CRS
1976	0.979 (0.953) CRS	0.953 (0.964) **DRS**	0.932 (0.955) **IRS**	1.000 (0.924) CRS	0.925 (0.954) **IRS**	0.988 (0.955) CRS	1.000 (0.956) CRS	1.000 (0.901) CRS	1.000 (0.892) CRS
1982	0.968 (0.968) CRS	0.994 (0.966) CRS	0.865 (0.889) **IRS**	0.968 (0.957) CRS	0.982 (0.967) CRS	1.000 (0.924) CRS	1.000 (0.963) CRS	0.993 (0.934) CRS	0.999 (0.962) CRS
1988	0.970 (0.978) **IRS**	0.992 (0.976) CRS	0.847 (0.927) **IRS**	0.971 (0.966) CRS	0.977 (0.970) CRS	1.000 (0.965) CRS	1.000 (0.977) CRS	0.975 (0.947) CRS	0.995 (0.980) CRS
1992	0.981 (0.971) CRS	0.961 (0.960) CRS	0.890 (0.912) **IRS**	0.880 (0.969) **IRS**	0.968 (0.953) CRS	1.000 (0.936) CRS	1.000 (0.868) CRS	0.952 (0.925) CRS	0.979 (0.975) CRS
1994	0.981 (0.976) CRS	0.965 (0.963) CRS	0.891 (0.912) **IRS**	0.884 (0.972) **IRS**	0.969 (0.955) CRS	1.000 (0.943) CRS	1.000 (0.876) CRS	0.952 (0.921) CRS	0.979 (0.978) CRS
1998	0.984 (0.980) CRS	0.964 (0.973) **DRS**	0.899 (0.921) **IRS**	0.912 (0.976) **IRS**	0.977 (0.966) CRS	1.000 (0.955) CRS	1.000 (0.867) CRS	0.952 (0.932) CRS	0.982 (0.977) CRS
2002	1.000 (0.895) CRS	0.965 (0.911) CRS	0.765 (0.850) **IRS**	0.867 (0.962) **IRS**	0.979 (0.950) CRS				

Critical Value (alpha = 0.01) in parentheses

Note: Only years in which survey was conducted for both Oregon and Washington (and 2002) are shown.

Table 18: Productivity Change, 1968-1982

Region	Productivity Change			Technical Progress			Efficiency Change		
	Annual Change	Lower 95%	Upper 95%	Annual Change	Lower 95%	Upper 95%	Annual Change	Lower 95%	Upper 95%
1	1.19%	1.00%	1.35%	0.82%	0.70%	1.04%	0.36%	0.04%	0.50%
2	1.05%	0.82%	1.14%	0.77%	0.69%	0.99%	0.27%	-0.12%	0.35%
3	1.35%	1.23%	1.88%	0.62%	0.27%	0.91%	0.73%	0.50%	1.45%
4	0.03%	-0.43%	0.20%	0.65%	0.39%	1.00%	-0.62%	-1.28%	-0.41%
5	0.58%	0.34%	0.85%	0.62%	0.48%	0.98%	-0.04%	-0.49%	0.17%
6	0.46%	0.07%	0.61%	0.56%	0.42%	0.94%	-0.11%	-0.77%	0.01%
7	0.59%	0.32%	0.98%	0.59%	0.21%	0.83%	0.00%	-0.42%	0.61%
8	0.39%	-0.08%	0.49%	0.50%	0.31%	0.89%	-0.11%	-0.88%	0.02%
9	-0.51%	-1.14%	-0.43%	0.50%	0.19%	0.90%	-1.02%	-1.82%	-0.84%
PNW	0.50%	0.13%	0.65%	0.61%	0.41%	0.93%	-0.12%	-0.69%	0.08%
OR	0.19%	-0.27%	0.35%	0.52%	0.27%	0.89%	-0.33%	-1.03%	-0.10%
WA	0.97%	0.73%	1.12%	0.75%	0.63%	0.99%	0.22%	-0.18%	0.37%

Table 19: Productivity Change, 1982-1992

Region	Productivity Change			Technical Progress			Efficiency Change		
	Annual Change	Lower 95%	Upper 95%	Annual Change	Lower 95%	Upper 95%	Annual Change	Lower 95%	Upper 95%
1	1.03%	0.99%	1.44%	0.69%	0.42%	0.86%	0.34%	0.21%	0.93%
2	0.44%	0.42%	0.71%	0.38%	0.28%	0.58%	0.06%	-0.04%	0.31%
3	-0.77%	-1.37%	-0.64%	0.82%	0.60%	1.36%	-1.59%	-2.62%	-1.39%
4	0.51%	0.46%	0.96%	0.43%	0.22%	0.71%	0.08%	-0.15%	0.66%
5	0.82%	0.71%	1.18%	0.59%	0.41%	0.87%	0.23%	-0.01%	0.65%
6	0.06%	-0.02%	0.32%	0.27%	0.17%	0.51%	-0.22%	-0.40%	0.02%
7	0.61%	0.26%	1.01%	0.61%	0.40%	1.14%	0.00%	-0.74%	0.48%
8	0.87%	0.82%	1.31%	0.72%	0.40%	0.87%	0.15%	0.02%	0.81%
9	-0.36%	-0.45%	0.04%	0.30%	0.15%	0.63%	-0.66%	-0.93%	-0.24%
PNW	0.50%	0.40%	0.86%	0.52%	0.33%	0.78%	-0.01%	-0.26%	0.42%
OR	0.47%	0.33%	0.87%	0.55%	0.32%	0.85%	-0.09%	-0.41%	0.43%
WA	0.54%	0.48%	0.85%	0.47%	0.33%	0.70%	0.07%	-0.09%	0.41%

Table 20: Productivity Change, 1992-2002

Region	Productivity Change			Technical Progress			Efficiency Change		
	Annual Change	Lower 95%	Upper 95%	Annual Change	Lower 95%	Upper 95%	Annual Change	Lower 95%	Upper 95%
1	1.13%	0.88%	1.62%	1.01%	0.54%	1.28%	0.13%	-0.32%	0.99%
2	1.30%	1.21%	1.62%	0.94%	0.66%	1.08%	0.36%	0.21%	0.87%
3	0.64%	0.51%	1.11%	1.40%	0.98%	1.59%	-0.76%	-0.97%	0.04%
4	-0.70%	-1.04%	-0.45%	1.25%	1.03%	1.61%	-1.96%	-2.49%	-1.64%
5	1.36%	1.16%	1.76%	0.94%	0.71%	1.30%	0.42%	0.06%	0.87%
6	-0.30%	-0.45%	0.48%	0.87%	0.35%	1.33%	-1.18%	-1.50%	-0.01%
7	2.16%	1.52%	2.89%	2.16%	1.31%	2.70%	0.00%	-0.91%	1.37%
8	0.15%	-0.47%	0.63%	1.23%	0.78%	1.91%	-1.08%	-2.11%	-0.34%
9	1.87%	1.62%	2.48%	1.21%	0.92%	1.78%	0.66%	0.04%	1.32%
PNW	0.99%	0.67%	1.49%	1.20%	0.76%	1.59%	-0.21%	-0.74%	0.58%
OR	0.83%	0.35%	1.46%	1.39%	0.84%	1.97%	-0.57%	-1.36%	0.41%
WA	1.17%	1.02%	1.53%	0.98%	0.67%	1.18%	0.19%	-0.05%	0.77%

Table 21: Comparison of Productivity Growth Estimates to Two Other DEA-based Sawmill Studies

Index	U.S. Pacific Northwest (1974-1992)*			Norway (1974-1991)	Washington State (1970-1998)**
	Point Estimate	Lower Bound of 95% CI	Upper Bound of 95% CI	Nyrud & Baardsen (2002)	Helvoigt & Grosskopf (2005)
Productivity	0.78%	0.64%	0.92%	0.82%	0.98%
Technical Progress	0.75%	0.62%	0.90%	0.29%	1.11%
Efficiency Change	0.03%	-0.19%	0.19%	0.47%	-0.14%

*Based on average of the nine regions weighted by 1992 lumber output.

** Because of the small number of data in each cross section, the “1970” period consisted of data for 1968, 1970, and 1972 and the “1998” period consisted of data for 1996, 1998, and 2000.

Table 22: Comparison of RTS Estimates Based on Stochastic Frontier Analysis and Data Envelopment Analysis

SFA (Chapter 3)				Data Envelopment Analysis			
Period	**RTS**	**St. Err.***	**Decision**	**Year**	**CRS Regions**	**IRS Regions**	**DRS Regions**
1970s (1968-1978)	0.981	0.041	CRS	**1968**	2, 4, 6, 7, 8, 9	1, 3, 5	
				1972	2, 6, 7, 8, 9	1, 3, 4, 5	
				1976	1, 4, 6, 7, 8, 9	3, 5	2
1980s (1980-1988)	1.029	0.040	CRS	**1982**	1, 2, 4, 5, 6, 7, 8, 9	3	
				1988	2,4,5,6,7,8,9	1, 3	
1990s (1990-2002)**	1.071	0.037	CRS	**1992**	1,2,5,6,7,8,9	3,4	
				1994	1,2,5,6,7,8,9	3,4	
				1998	1,5,6,7,8,9	3,4	2
				2002**	1,2,5	3,4	

* Asymptotic standard error. The null hypothesis is RTS = 1.0, vs. the alternative hypothesis RTS ≠ 1.0 (2-sided test). The critical value from the t-distribution with infinite dof and alpha = 0.5 is 1.96. Thus, one cannot reject the null hypothesis of CRS.

** Data for Oregon run through 1998 only

Table 23: Comparison of Average Annual Productivity Growth, Efficiency Change, and Technical Progress in the Pacific Northwest Sawmill Industry

Time Period	Economic Measure	SFPF (Chapter 3)			DEA		
		Point Estimate	Lower Bound (95% CI)	Upper Bound (95% CI)	Point Estimate	Lower Bound (95% CI)	Upper Bound (95% CI)
1970s (Period 1)	Prod. Growth*	1.60%	1.01%	2.19%	0.50%	0.13%	0.65%
	Eff. Change	-0.02%	St. error not computed		-0.12%	-0.69%	0.08%
	Tech. Prog.	1.60%	1.01%	2.19%	0.61%	0.41%	0.93%
1980s (Period 2)	Prod. Growth*	1.90%	1.31%	2.49%	0.50%	0.40%	0.86%
	Eff. Change	-0.28%	St. error not computed		-0.01%	-0.26%	0.42%
	Tech. Prog.	2.10%	1.51%	2.69%	0.52%	0.33%	0.78%
1990s (Period 3)	Prod. Growth*	2.10%	1.12%	3.08%	0.99%	0.67%	1.49%
	Eff. Change	-0.33%	St. error not computed		-0.21%	-0.74%	0.58%
	Tech. Prog.	2.20%	1.42%	2.98%	1.20%	0.76%	1.59%

* Note 1: The SFPF estimates of productivity growth explicitly incorporate changes in scale efficiency, with DEA it is assumed that the DMUs operate at a point of CRS, thus changes in scale efficiency are not considered.

Note 2: The SFPF-based estimates of productivity growth incorporate technical progress, efficiency change, and changes in scale efficiency. The standard errors used to compute the confidence intervals for the true rate of (SFPF-based) productivity are based on estimates of productivity growth *exclusive* of efficiency change.

Table A1: Region 1 Technical Efficiency, Bias, 95% Confidence Interval

Year	Variable Returns to Scale (VRS)				Constant Returns to Scale (CRS)			
	TE	Bias-Adj	Low 95%	Up 95%	TE	Bias-Adj	Low 95%	Up 95%
1968	0.98	0.973	0.96	0.98	0.91	0.89	0.87	0.91
1970	0.97	0.963	0.95	0.97	0.92	0.91	0.89	0.92
1972	0.96	0.943	0.93	0.96	0.92	0.90	0.87	0.92
1974	0.99	0.979	0.97	0.99	0.96	0.95	0.93	0.96
1976	0.95	0.927	0.91	0.94	0.93	0.91	0.88	0.92
1978	0.94	0.919	0.90	0.93	0.92	0.90	0.88	0.91
1980	0.97	0.955	0.94	0.97	0.94	0.92	0.90	0.94
1982	0.98	0.966	0.96	0.98	0.95	0.94	0.93	0.95
1984	1.00	0.938	0.87	1.00	1.00	0.93	0.88	0.99
1986	1.00	0.980	0.97	1.00	0.99	0.97	0.96	0.98
1988	0.94	0.926	0.91	0.94	0.92	0.90	0.89	0.92
1990	0.93	0.912	0.90	0.92	0.90	0.88	0.87	0.89
1992	1.00	0.958	0.94	1.00	0.99	0.95	0.93	0.98
1994	1.00	0.957	0.92	1.00	1.00	0.96	0.93	0.99
1996	1.00	0.970	0.94	1.00	1.00	0.97	0.94	0.99
1998	0.91	0.882	0.84	0.91	0.89	0.85	0.81	0.88
2000	0.96	0.938	0.91	0.95	0.94	0.91	0.89	0.93
2002	1.00	0.935	0.90	1.00	1.00	0.93	0.91	0.99

Table A2: Region 2 Technical Efficiency, Bias, 95% Confidence Interval

Year	Variable Returns to Scale (VRS)				Constant Returns to Scale (CRS)			
	TE	Bias-Adj	Low 95%	Up 95%	TE	Bias-Adj	Low 95%	Up 95%
1968	0.92	0.91	0.90	0.92	0.92	0.90	0.87	0.91
1970	0.92	0.92	0.91	0.92	0.92	0.91	0.89	0.92
1972	1.00	0.99	0.98	1.00	0.95	0.93	0.91	0.95
1974	0.96	0.95	0.93	0.96	0.96	0.95	0.94	0.96
1976	0.97	0.94	0.91	0.96	0.93	0.91	0.89	0.92
1978	1.00	0.98	0.97	1.00	0.93	0.92	0.90	0.93
1980	0.92	0.90	0.88	0.91	0.92	0.91	0.89	0.91
1982	0.95	0.94	0.93	0.95	0.95	0.95	0.94	0.95
1984	0.97	0.95	0.94	0.96	0.90	0.88	0.87	0.89
1986	1.00	0.98	0.97	1.00	0.94	0.92	0.91	0.93
1988	1.00	0.97	0.94	1.00	0.95	0.94	0.93	0.95
1990	0.95	0.93	0.91	0.95	0.92	0.90	0.88	0.92
1992	0.99	0.97	0.96	0.98	0.96	0.94	0.93	0.96
1994	1.00	0.98	0.96	1.00	0.96	0.95	0.93	0.96
1996	1.00	0.94	0.90	1.00	1.00	0.97	0.95	0.99
1998	1.00	0.95	0.90	1.00	0.94	0.91	0.89	0.94
2000	1.00	0.96	0.92	1.00	0.92	0.90	0.88	0.92
2002	1.00	0.93	0.89	1.00	0.99	0.96	0.94	0.99

Table A3: Region 3 Technical Efficiency, Bias, 95% Confidence Interval

Year	Variable Returns to Scale (VRS)				Constant Returns to Scale (CRS)			
	TE	Bias-Adj	Low 95%	Up 95%	TE	Bias-Adj	Low 95%	Up 95%
1968	1.00	0.98	0.93	1.00	0.90	0.88	0.86	0.90
1970	1.00	0.97	0.93	1.00	0.87	0.86	0.84	0.87
1972	1.00	0.97	0.92	1.00	0.90	0.88	0.85	0.90
1974	1.00	0.97	0.94	1.00	0.93	0.93	0.91	0.93
1976	1.00	0.94	0.87	1.00	0.99	0.96	0.94	0.98
1978	0.96	0.93	0.88	0.95	0.89	0.87	0.85	0.88
1980	1.00	0.94	0.87	1.00	0.90	0.88	0.86	0.90
1982	1.00	0.94	0.87	1.00	1.00	0.95	0.91	1.00
1984	1.00	0.94	0.87	1.00	0.97	0.95	0.93	0.97
1986	1.00	0.93	0.85	1.00	0.95	0.92	0.91	0.94
1988	0.95	0.93	0.90	0.95	0.87	0.86	0.85	0.87
1990	1.00	0.95	0.90	1.00	0.91	0.88	0.86	0.90
1992	1.00	0.93	0.86	1.00	0.85	0.84	0.82	0.85
1994	1.00	0.93	0.86	1.00	0.86	0.84	0.83	0.85
1996	1.00	0.93	0.86	1.00	0.83	0.81	0.78	0.83
1998	1.00	0.93	0.85	1.00	0.77	0.73	0.70	0.76
2000	1.00	0.93	0.87	1.00	0.90	0.86	0.84	0.89

Table A4: Region 4 Technical Efficiency, Bias, 95% Confidence Interval

Year	Variable Returns to Scale (VRS)				Constant Returns to Scale (CRS)			
	TE	Bias-Adj	Low 95%	Up 95%	TE	Bias-Adj	Low 95%	Up 95%
1968	1.00	0.98	0.93	1.00	0.92	0.89	0.84	0.92
1970	1.00	0.98	0.93	1.00	0.97	0.96	0.93	0.97
1972	1.00	0.97	0.92	1.00	1.00	0.93	0.88	1.00
1974	1.00	0.96	0.91	1.00	0.99	0.98	0.96	0.99
1976	1.00	0.95	0.90	1.00	1.00	0.94	0.91	0.99
1978	0.93	0.91	0.89	0.93	0.92	0.91	0.89	0.92
1980	0.94	0.92	0.90	0.94	0.92	0.90	0.89	0.91
1982	0.90	0.88	0.86	0.89	0.84	0.83	0.81	0.84
1984	0.98	0.96	0.94	0.97	0.94	0.93	0.91	0.94
1986	0.96	0.95	0.94	0.96	0.91	0.90	0.89	0.91
1988	0.92	0.90	0.89	0.92	0.85	0.83	0.82	0.84
1990	0.95	0.93	0.91	0.95	0.83	0.81	0.79	0.82
1992	1.00	0.93	0.89	1.00	0.85	0.82	0.80	0.85
1994	1.00	0.97	0.94	1.00	0.86	0.85	0.83	0.86
1996	1.00	0.94	0.89	1.00	0.88	0.85	0.84	0.87
1998	1.00	0.93	0.84	1.00	0.88	0.85	0.83	0.88
2000	0.87	0.84	0.82	0.87	0.68	0.66	0.63	0.68
2002	0.80	0.78	0.76	0.80	0.70	0.68	0.67	0.70

Table A5: Region 5 Technical Efficiency, Bias, 95% Confidence Interval

Year	Variable Returns to Scale (VRS)				Constant Returns to Scale (CRS)			
	TE	Bias-Adj	Low 95%	Up 95%	TE	Bias-Adj	Low 95%	Up 95%
1968	1.00	0.98	0.93	1.00	0.89	0.87	0.84	0.89
1970	0.94	0.93	0.92	0.94	0.87	0.86	0.85	0.87
1972	0.92	0.90	0.89	0.92	0.87	0.85	0.84	0.86
1974	0.97	0.96	0.95	0.97	0.93	0.92	0.91	0.93
1976	0.98	0.95	0.92	0.97	0.95	0.93	0.91	0.95
1978	0.91	0.89	0.87	0.91	0.90	0.89	0.88	0.90
1980	0.93	0.91	0.89	0.93	0.92	0.91	0.90	0.92
1982	0.98	0.95	0.91	0.98	0.89	0.88	0.86	0.89
1984	0.99	0.97	0.95	0.98	0.98	0.96	0.95	0.98
1986	0.98	0.96	0.95	0.98	0.97	0.96	0.95	0.97
1988	0.98	0.96	0.94	0.98	0.98	0.96	0.94	0.98
1990	1.00	0.97	0.95	1.00	0.97	0.93	0.91	0.96
1992	0.92	0.90	0.88	0.92	0.91	0.89	0.87	0.91
1994	0.98	0.96	0.95	0.98	0.95	0.93	0.92	0.95
1996	0.89	0.87	0.86	0.89	0.85	0.83	0.82	0.85
1998	0.97	0.95	0.92	0.97	0.94	0.91	0.89	0.94
2000	1.00	0.97	0.94	1.00	0.99	0.97	0.95	0.99
2002	0.97	0.95	0.92	0.96	0.95	0.93	0.90	0.95

Table A6: Region 6 Technical Efficiency, Bias, 95% Confidence Interval

Year	Variable Returns to Scale (VRS)				Constant Returns to Scale (CRS)			
	TE	Bias-Adj	Low 95%	Up 95%	TE	Bias-Adj	Low 95%	Up 95%
1968	1.00	0.98	0.94	1.00	1.00	0.96	0.92	1.00
1972	0.98	0.97	0.95	0.98	0.98	0.96	0.93	0.98
1976	1.00	0.94	0.90	1.00	1.00	0.94	0.91	0.99
1982	1.00	0.98	0.97	1.00	0.99	0.97	0.96	0.98
1985	1.00	0.97	0.94	1.00	1.00	0.96	0.94	0.99
1988	1.00	0.96	0.93	1.00	1.00	0.95	0.93	0.99
1992	0.98	0.97	0.96	0.98	0.96	0.95	0.94	0.96
1994	0.99	0.97	0.96	0.99	0.98	0.96	0.95	0.97
1998	0.98	0.95	0.93	0.98	0.97	0.94	0.92	0.97

Table A7: Region 7 Technical Efficiency, Bias, 95% Confidence Interval

Year	Variable Returns to Scale (VRS)				Constant Returns to Scale (CRS)			
	TE	Bias-Adj	Low 95%	Up 95%	TE	Bias-Adj	Low 95%	Up 95%
1968	1.00	0.98	0.96	1.00	1.00	0.97	0.93	1.00
1972	1.00	0.97	0.92	1.00	1.00	0.94	0.90	1.00
1976	1.00	0.96	0.92	1.00	1.00	0.95	0.92	0.99
1982	1.00	0.96	0.93	1.00	1.00	0.95	0.92	0.99
1985	1.00	0.95	0.92	1.00	1.00	0.94	0.92	0.99
1988	1.00	0.93	0.87	1.00	1.00	0.92	0.87	0.99
1992	1.00	0.96	0.94	1.00	1.00	0.96	0.94	0.99
1994	1.00	0.96	0.93	1.00	1.00	0.95	0.92	0.99
1998	1.00	0.93	0.86	1.00	1.00	0.91	0.86	0.99

Table A8: Region 8 Technical Efficiency, Bias, 95% Confidence Interval

Year	Variable Returns to Scale (VRS)				Constant Returns to Scale (CRS)			
	TE	Bias-Adj	Low 95%	Up 95%	TE	Bias-Adj	Low 95%	Up 95%
1968	1.00	0.98	0.93	1.00	1.00	0.95	0.91	1.00
1972	1.00	0.97	0.93	1.00	0.98	0.96	0.94	0.98
1976	1.00	0.94	0.88	1.00	1.00	0.97	0.93	1.00
1982	0.99	0.97	0.95	0.98	0.99	0.97	0.96	0.98
1985	1.00	0.94	0.90	1.00	1.00	0.98	0.95	1.00
1988	1.00	0.94	0.90	0.99	0.97	0.94	0.92	0.96
1992	1.00	0.95	0.93	1.00	1.00	0.95	0.94	0.99
1994	1.00	0.96	0.93	1.00	1.00	0.96	0.94	0.99
1998	1.00	0.95	0.92	1.00	0.98	0.94	0.91	0.98

Table A9: Region 9 Technical Efficiency, Bias, 95% Confidence Interval

Year	Variable Returns to Scale (VRS)				Constant Returns to Scale (CRS)			
	TE	Bias-Adj	Low 95%	Up 95%	TE	Bias-Adj	Low 95%	Up 95%
1968	1.00	0.98	0.93	1.00	1.00	0.94	0.90	1.00
1972	0.90	0.89	0.88	0.90	0.89	0.87	0.84	0.89
1976	1.00	0.96	0.93	1.00	1.00	0.97	0.95	0.99
1982	0.87	0.85	0.84	0.87	0.87	0.85	0.84	0.87
1985	0.88	0.85	0.84	0.87	0.88	0.86	0.84	0.87
1988	0.89	0.87	0.86	0.88	0.87	0.86	0.84	0.87
1992	0.83	0.81	0.79	0.82	0.81	0.79	0.78	0.81
1994	0.85	0.84	0.83	0.85	0.85	0.84	0.83	0.85
1998	0.91	0.89	0.87	0.90	0.90	0.88	0.86	0.90

Figure 9: Best Practices Frontier in Input Space

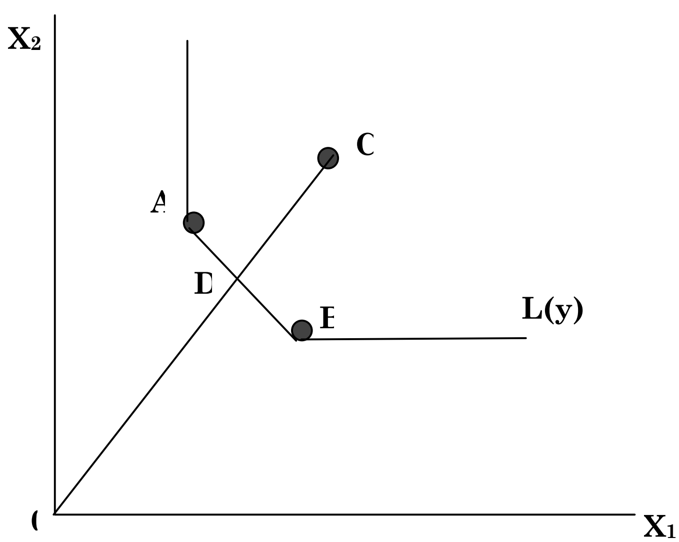


Figure 10: Production Functions Showing CRS and VRS Technologies

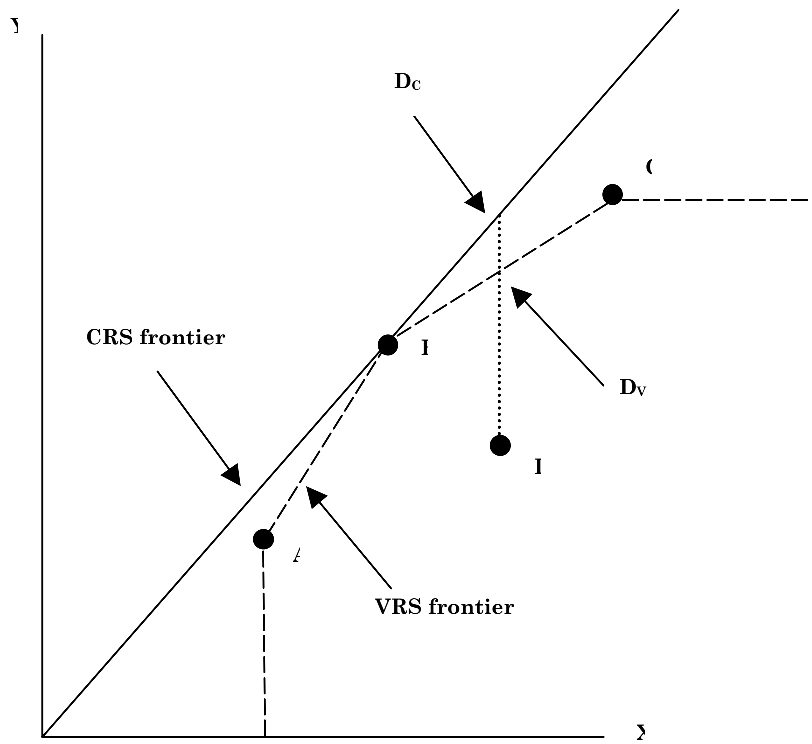


Figure 11: Pacific Northwest Sawmill Regions

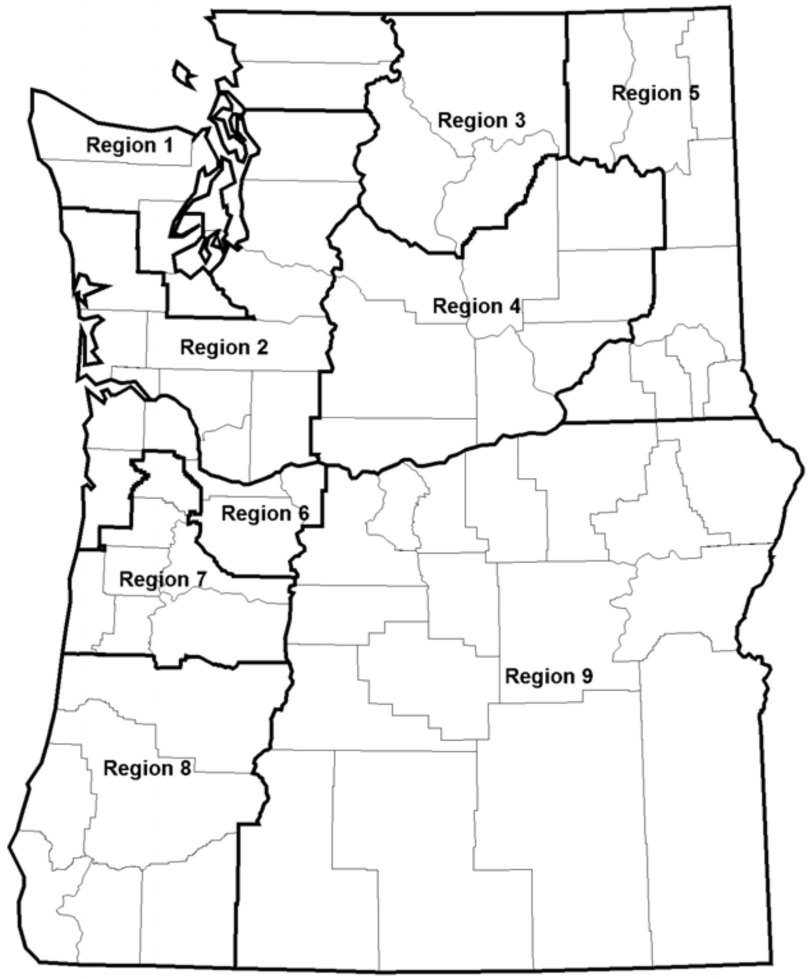


Figure 12: DEA-based Technical Efficiency Estimates Assuming CRS Production Function: Lumber Volume-Weighted Mean and Min-Max Range

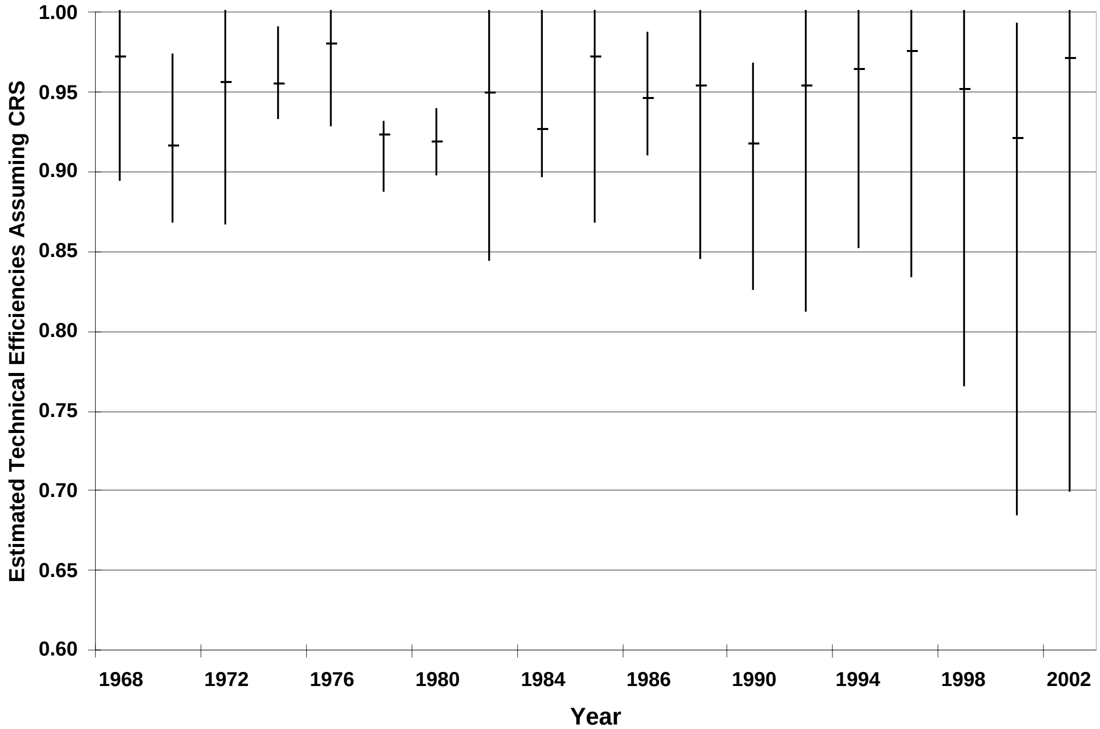
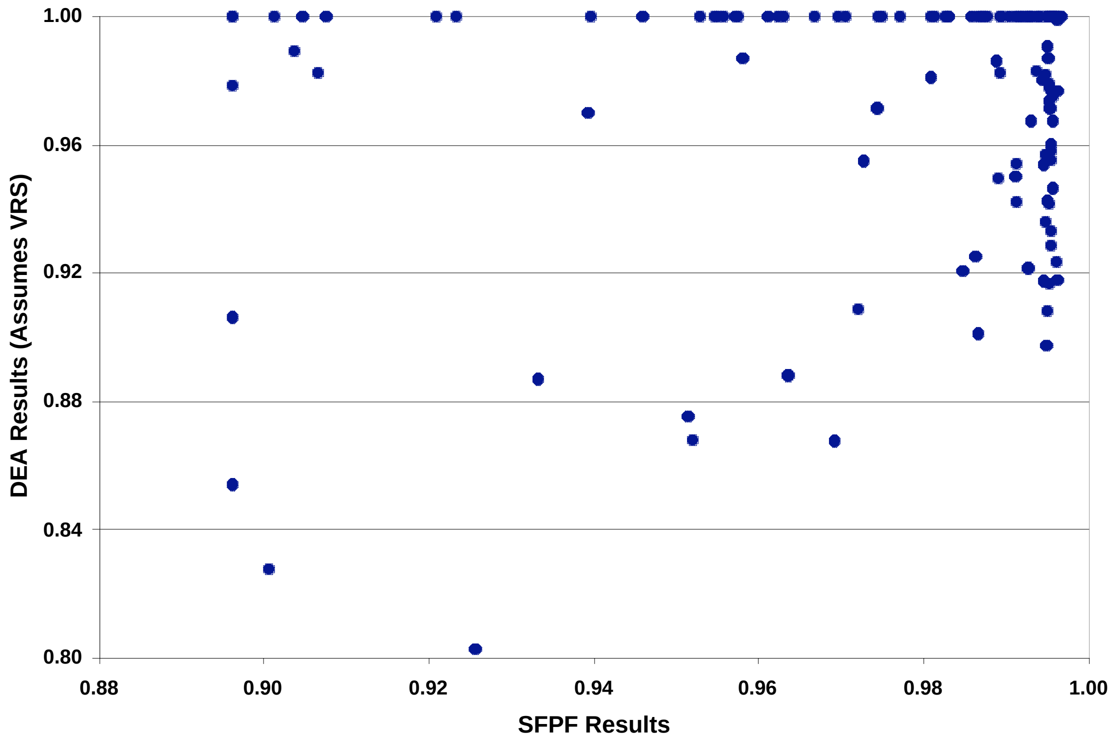


Figure 13: Scatter Plot of SFPF and DEA Technical Efficiency Estimates (each point is a DMU for a Specific Year)



RELATIONSHIP TO HISTORICAL LITERATURE

The econometric studies of the Pacific Northwest and Canadian sawmilling industry discussed in chapters 2, 3, and 4 were based on data that, at most, overlap only the first half of the study period examined in these chapters. Therefore, comparisons of results are limited to only these earlier years. Constantino and Haley (1988) found that over the period 1957-1981, technical change averaged 0.6% per year for the British Columbia coast and the U.S. Pacific Northwest. Unfortunately, the authors did not provide technical change estimates for just the last decade of their analysis, so truly meaningful comparison is not possible. Abt (1987) did not provide estimates of productivity or technical change, but found that the industry operated under CRS between 1963 and 1978.

Merrifield and Haynes (1985) concluded that over the period 1950-1979, technical change was "slight." Based on data for 1955-1979, Merrifield and Singleton (1986) found technical change in the U.S. PNW sawmilling industry to have a capital-using and labor-saving bias. These results are consistent with the results of the stochastic frontier production function analysis of Chapter 3. Meil and Nautiyal (1988) found no significant increases in productivity between 1968 and 1984 for the British Columbia coast or interior. Stevens (1995) reported "neutral" technical change occurred in western Washington between 1980 and 1988, but the author did not report the rate of technical change.

According to Stevens (1991), the sawmilling industry in western Washington made little investment in machinery and equipment between 1980 and 1988, and little technical change occurred over the period. He found that technical change was capital saving and *skilled* labor-using. Stevens' findings appear to be contrary to the general results of chapters 2 and 4 (i.e., of positive technical change), and specifically contradictory to Chapter 3, in which technical change for the Northwest sawmilling industry was found to be capital-using and labor-saving. In all three studies technical change and productivity growth was statistically significant and positive during the 1980s. The discrepancy in findings may be due to the slight difference in time periods considered and/or to the larger geography considered in these analyses. It is also important to point out that Stevens (1991) finding of labor-using technical change was specific to skilled labor.

Finally, it is important to place the three analyses presented in this thesis into an historical context. Over the past four decades, forest economists have employed increasingly sophisticated econometric and mathematical programming techniques in their analysis of the forest products industry. Application of such techniques by forest economists often occurs subsequent to widespread acceptance by general economists. This is certainly the case with DEA and SFA. Though the foundations of each of these techniques were well established by 1990, there have been relatively few analyses in the forest economics literature in which these methods have been employed. To the best of our knowledge, Carter and Cubbage (1995) were the first to apply SFA in a forestry context and Nyrud and Baardsen (2003) were the first to apply DEA. Although there are still only a handful of frontier-based economic analyses that examine the production structure and technical and productivity growth in the forest products industry, the number will certainly grow. In Stier and Bengston's (1992) review of econometric analyses of the forest products industry, the authors classify studies as first-, second-, or third-generation approaches. Each study's designation is based on its degree of sophistication in representing the production and/or profit and cost structure of the respective forest products sector. Following the Stier and Bengston's classification system, production-oriented, frontier-based techniques can be thought of as a fourth-generation approach. DEA and SFA bring the reality to empirical economic analysis that producers, despite their best efforts, often do not successfully operate on their respective production frontier. As this "fourth-generation" of analyses becomes increasingly established in the literature, forest economist will likely move on to frontier-based cost and profit function analyses—i.e., "fifth-generation" studies.

Conclusions

There have been few analyses over the past decade that have examined the structure of production in the U.S. Pacific Northwest sawmilling industry and no analysis that has employed frontier-based estimation methods. A consequence of this gap in the empirical literature is that statements made by policy makers, the public, and industry representatives regarding changes in productivity or advances in technology in the sawmilling industry may be based on the observation of individual producers, anecdotal information, or merely speculation. The three analyses comprising this project bridge this information gap by providing a thorough examination of changes in the production structure of the Northwest sawmilling industry. In doing so, these studies provide answers to the five questions posed in the introduction.[96]

1. **How has the average rate of technical efficiency in the Northwest sawmilling industry changed during the 1968 to 2002 time period?**

Technical efficiency is measured relative to the efficient frontier at a certain point in time. Therefore, assuming the production frontier is shifting over time, estimates of technical efficiency are not directly comparable across time. Nevertheless, comparing the technical efficiency of a particular region provides insight into how that region performed, relative to the most efficient regions. Likewise, comparing the (weighted) average technical efficiency of all regions over time provides insight into how the "average" region performed, relative to the most efficient regions.

On a period-by-period basis the relative technical efficiency of each sawmilling region was estimated in the DEA and SFA studies. The range of these efficiency scores increased over time. DEA and SFA differed in the size of this

[96] The answers to these questions are "generally" based on all three analyses, but specific estimates are based on chapters 3 and 4.

range, with maximum DEA range extending from 0.7 to 1.0 and the maximum SFA range extending from 0.88 to 0.99. The increase in the range of scores was due to decreases in the minimum technical efficiency, as the maximum score (given the nature of DEA and SFA) was consistently at or near 1.0. Based on the DEA results, the (weighted) average technical efficiency of the Northwest sawmill industry remained roughly constant or even increased slightly over the study period. Conversely, based on the SFA results, the geometric mean technical efficiency declined slightly over the period, but remained above 0.95 in all years.[97]

2. **Has the sawmilling industry operated at a scale efficient level during this period?**

The results of the SFA-based study indicate the null hypothesis of constant returns to scale (CRS) (i.e., scale efficiency) could not be rejected for Northwest sawmilling industry. This is despite the fact that the point estimates of returns to scale increases from 0.98 in the 1970s to 1.03 in the 1980s and 1.07 in the 1990s. In the DEA-based study, returns to scale were examined for each of the nine regions. The results indicated that the four Oregon regions operated at a point of CRS in all years examined and the two western Washington regions operated a point of CRS for most years. North central Washington, the smallest of the nine sawmill regions, was found to operate at a point of increasing returns to scale (IRS) in all years examined. South central Washington and the Inland Empire were found to operate at points of either CRS or IRS.

3. **What has been the rate of productivity growth during the 1968 to 2002 time period?**

The methods used to estimate growth in total factor productivity differ between DEA and SFA, but the resulting estimates are comparable. In DEA,

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[97] Note, the weighted average technical efficiencies computed from the SFA results were not effectively different from the geometric mean technical efficiencies.

the Malmquist productivity index was computed based on estimates of distance functions. In SFA, time-based technology parameters were estimated and calculus was used to estimate productivity change. The results from both the DEA and SFA analyses indicated that productivity growth was positive throughout the study period, ranging from approximately 0.65% per year in the DEA study to approximately 1.8% per year in the SFA study. The difference in the magnitude of productivity growth estimated from the two methods is somewhat disconcerting. Confidence intervals were constructed for each of the estimates of productivity growth, but the two intervals do not overlap. The conclusion to draw from this is that the two studies represent independent estimates of productivity growth and their respective magnitudes represent upper and lower bounds on the productivity growth rate.

4. **How have the three components of productivity change (i.e., technical change, efficiency change, and scale efficiency change) impacted productivity growth over this period?**

Productivity growth can occur due to three separate phenomena: 1. Technical change (i.e., expansion of the production frontier), 2. Efficiency change (i.e., DMUs adopting the existing "best practices" technology), and 3. Scale efficiency change (i.e., DMUs moving from a point of increasing or decreasing returns to scale to a point of constant returns to scale). The results of both the DEA and SFA studies indicate that the vast majority of productivity growth in the Northwest sawmilling industry between 1968 and 2002 was due to technical change. Improvements in scale efficiency played a very small role in productivity growth, and efficiency change was zero or even negative. Negative efficiency change indicates that, even as the industry's production frontier expanded over the past 30 years, the distance of the average DMU to the industry's production frontier actually increased. The results of the SFA study indicate that technical change was labor-saving and capital-using, and was neutral with respect to sawlog usage.

5. **Has the substitutability relationship between inputs changed over the period and if so, how?**

From the SFA study, Morishima elasticities of substitution were computed for each pair of inputs based on the mean value of the data for the 1970s, 1980s, 1990s, and over the entire study period. Consistent across each of the time periods, labor was not substitutable for the other inputs. Thus, an increase in the relative price of sawlogs, capital, or *other inputs* would not result in substituting more labor for any of these other inputs. The converse was not true. Capital was found to be consistently substitutable for labor. Sawlogs were found to be a complement to labor in the 1970s, but substitutable for labor in the subsequent decades. This is likely due to decreasing sawlog size. Smaller sawlogs are more amenable to mechanization, which is labor saving.

6. **Do the DEA and SFA analyses provide corroborating or contradicting findings?**

The final purpose of this study was to compare the DEA-based results with those obtained using SFA methods. While there is a small but growing literature devoted to comparative analysis of the SFA and DEA techniques, I know of no studies that compare the two techniques with respect to productivity growth and its components. In comparing the results of the DEA and SFA studies, I found that the DEA-based estimates of technical efficiency neither corroborate, nor contradict the SFPF-based estimate of technical efficiency, but rather improved upon the SFPF estimates. With respect to returns to scale, DEA corroborates the results obtained through SFPF and, perhaps, improved upon those results by providing region-level estimates. With respect to efficiency change, DEA clearly corroborates the results obtained through SFPF. For productivity growth and technical progress, the DEA estimates were substantially lower than those obtained through SFPF. This is an important finding and one that should lead to caution when relying on the results derived from only one of the two methods. It is unclear why productivity growth and technical progress estimates differed so substantially between the two methods.

This project is the first to employ DEA and SFA to examine technical efficiency, scale efficiency, and productivity growth and its decomposition in the Northwest sawmilling industry. These two methods allowed for the relaxation of the typical economic assumptions that lumber producers were successful cost minimizers and/or profit maximizers. Thus, instead of estimating the average production function, DEA and SFA allowed us to estimate the production frontier and provide estimates of each DMU's inefficiency, relative to that frontier. This project is also among the first empirical studies to employ the bootstrap methods developed by Simar and Wilson (1998, 1999, 2000a, 2000b, 2002) in order to construct confidence intervals and perform hypothesis testing on DEA estimates. Simar and Wilson's bootstrapping technique eliminates the primary criticism of all DEA-based analyses—the ability to draw statistical inference.

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APPENDIX: STUDY DATA

Appendix Table 1: Oregon & Washington Sawmill Production Data

Year	Region	Capacity	Sawlogs	SIC 242 Employment	Other	Lumber	Operating Days	Shifts
1968	1	1,509	400,024	1,981	3,459,388	450,514	234	1.53
1970	1	1,585	319,348	1,749	3,233,221	397,706	224	1.60
1972	1	1,769	371,976	1,971	4,088,077	500,083	238	1.72
1974	1	1,894	341,287	2,255	3,236,289	444,643	225	1.76
1976	1	1,935	386,465	2,487	3,434,627	526,659	236	1.80
1978	1	1,868	421,433	2,836	4,288,657	598,128	236	1.78
1980	1	1,751	315,553	2,427	3,081,701	466,326	229	1.78
1982	1	1,582	305,913	1,992	2,776,837	437,686	216	1.81
1984	1	1,616	212,031	1,894	2,703,043	380,307	219	1.64
1986	1	1,572	325,794	1,948	3,633,047	522,622	242	1.92
1988	1	1,682	341,341	2,189	3,647,607	523,698	240	2.07
1990	1	1,614	335,536	1,895	3,670,222	506,684	242	1.91
1992	1	1,772	329,277	1,639	3,784,452	580,168	255	1.84
1994	1	2,615	350,137	1,540	4,682,238	640,135	249	1.82
1996	1	2,791	357,895	1,607	6,054,067	662,842	259	1.79
1998	1	2,153	361,725	1,577	6,016,744	680,419	255	1.86
2000	1	2,370	408,058	1,678	6,762,268	810,524	251	1.98
2002	1	2,126	453,138	1,609	6,997,056	937,475	248	1.98
1968	2	6,151	1,725,419	12,243	15,617,034	2,033,797	243	1.75
1970	2	6,436	1,558,192	11,625	15,774,855	1,940,404	246	1.79
1972	2	6,516	1,703,585	12,810	18,735,243	2,291,830	248	1.84
1974	2	6,875	1,700,523	13,905	14,377,605	1,975,380	235	1.79
1976	2	7,610	1,867,580	14,600	15,235,906	2,336,244	241	1.83
1978	2	7,570	1,950,758	14,775	19,083,916	2,661,585	242	2.01
1980	2	7,686	1,486,516	12,514	13,121,565	1,985,568	222	1.87
1982	2	7,056	1,332,365	11,162	11,275,740	1,777,286	213	1.85
1984	2	7,951	1,643,419	11,459	16,495,023	2,320,782	220	1.89
1986	2	6,672	1,663,622	9,973	16,709,402	2,403,685	234	1.92
1988	2	7,608	1,930,866	11,574	19,762,933	2,837,424	244	1.94
1990	2	8,091	1,665,918	10,854	18,964,005	2,618,032	239	1.95
1992	2	7,524	1,565,604	9,526	16,408,343	2,515,449	241	1.95
1994	2	8,098	1,679,836	10,061	20,561,690	2,811,104	240	2.10
1996	2	7,124	1,607,769	10,334	26,025,312	2,849,435	242	2.06
1998	2	7,502	1,602,952	9,730	26,630,955	3,011,630	234	2.08
2000	2	8,460	1,584,031	8,873	24,872,828	2,981,252	235	2.11
2002	2	7,015	1,472,581	7,913	22,470,553	3,010,635	250	2.16
1968	3	1,033	333,614	1,373	2,742,441	349,702	240	1.63

Year	Region	Capacity	Sawlogs	SIC 242 Employment	Other	Lumber	Operating Days	Shifts
1970	3	776	169,561	680	1,574,182	196,319	225	1.79
1972	3	857	256,285	790	2,473,454	286,158	241	1.82
1974	3	894	215,947	946	1,925,773	257,972	243	1.81
1976	3	679	183,442	977	1,616,308	251,192	238	1.91
1978	3	878	202,076	1,142	1,896,888	269,014	235	1.90
1980	3	750	134,232	807	1,271,101	188,339	219	1.67
1982	3	842	136,045	489	1,208,333	168,332	167	1.76
1984	3	692	153,367	461	1,456,271	203,726	240	1.78
1986	3	365	106,688	697	893,383	136,030	249	2.58
1988	3	646	154,987	752	1,473,160	208,168	234	2.35
1990	3	407	121,788	1,005	1,347,970	165,955	247	2.14
1992	3	463	106,096	889	1,415,351	151,017	252	1.91
1994	3	483	103,709	909	1,681,061	153,244	250	1.79
1996	3	503	104,495	349	1,516,594	151,173	246	1.76
1998	3	623	89,957	364	1,458,778	141,759	227	1.92
2000	3	588	109,548	364	2,166,681	180,387	231	1.86
2002	3	407	90,290	342	1,581,184	142,834	234	2.00
1968	4	823	302,602	1,650	2,644,657	337,233	244	2.30
1970	4	850	253,935	1,543	2,568,081	320,270	248	2.24
1972	4	643	275,023	1,793	3,361,453	388,892	245	2.23
1974	4	710	212,939	1,570	2,097,446	280,969	229	2.04
1976	4	772	294,458	1,621	2,255,722	350,564	252	1.88
1978	4	940	276,817	1,849	2,437,346	345,661	241	2.05
1980	4	862	225,756	1,446	1,903,686	282,069	220	2.17
1982	4	947	194,540	1,178	1,795,545	250,136	202	1.85
1984	4	870	225,404	1,254	2,235,230	312,699	240	1.76
1986	4	1,540	270,103	1,140	2,443,474	372,053	245	1.65
1988	4	775	170,625	1,127	1,598,773	225,918	214	1.77
1990	4	835	182,661	921	2,062,198	253,887	226	1.85
1992	4	573	159,519	827	1,961,511	209,292	245	1.67
1994	4	608	137,051	897	2,193,055	199,917	234	1.74
1996	4	447	109,910	747	1,633,368	162,813	234	1.84
1998	4	386	112,642	677	1,658,105	161,129	226	1.91
2000	4	720	123,811	744	2,270,146	189,001	237	1.72
2002	4	963	149,281	893	2,461,156	222,325	220	1.62
1968	5	1,365	386,802	1,307	3,332,059	424,887	236	1.71
1970	5	1,119	292,152	1,217	2,539,912	316,757	234	1.77
1972	5	1,093	275,997	1,415	2,892,110	334,593	242	1.86
1974	5	1,199	292,161	1,459	2,680,198	359,033	230	1.84
1976	5	1,071	274,430	1,506	2,289,446	355,805	243	1.87
1978	5	1,096	282,859	1,836	2,564,557	363,702	242	2.21

Year	Region	Capacity	Sawlogs	SIC 242 Employment	Other	Lumber	Operating Days	Shifts
1980	5	1,019	247,193	1,562	2,235,163	331,184	225	2.40
1982	5	854	159,375	1,327	1,602,478	223,240	212	2.06
1984	5	1,196	331,308	1,760	3,405,251	476,380	238	2.21
1986	5	1,421	367,167	1,463	3,503,640	533,478	240	2.40
1988	5	1,444	417,016	1,756	4,246,694	600,088	259	2.13
1990	5	1,278	362,234	1,468	4,297,007	529,025	236	2.11
1992	5	1,396	351,136	1,835	4,852,044	517,710	241	2.02
1994	5	1,263	308,013	1,618	5,280,229	481,341	220	2.05
1996	5	1,071	253,635	1,239	3,653,366	364,165	239	2.08
1998	5	857	250,610	1,302	3,897,390	378,735	241	2.03
2000	5	926	277,952	1,231	5,070,086	422,110	245	2.07
2002	5	979	314,617	1,109	5,035,071	454,836	248	2.53
1968	6	3703	884178	3754	8,354,934	1199683	223	1.44
1972	6	4331	968613	3801	10,195,106	1348744	234	1.55
1976	6	3979	815092	4001	7,779,113	1283602	227	1.53
1982	6	2964	324108	2595	2,967,758	482897	181	1.60
1985	6	3214	695732	3159	6,713,214	1122249	233	1.66
1988	6	3633	829455	3281	9,419,464	1382723	233	1.66
1992	6	2125	396371	2448	3,926,457	627925	225	1.60
1994	6	1747	373372	2497	4,424,407	625159	225	1.73
1998	6	2836	691633	2431	9,175,667	1084209	229	1.79
1968	7	4539	905921	3626	8,339,550	1197474	229	1.42
1972	7	4641	877629	3262	9,940,089	1315007	232	1.53
1976	7	4558	778664	3551	6,962,950	1148930	226	1.50
1982	7	3765	599284	2657	5,181,078	843036	188	1.56
1985	7	4411	918908	3592	8,847,925	1479109	233	1.68
1988	7	5513	1139756	3793	13,419,220	1969864	237	1.60
1992	7	3805	693989	2794	7,464,548	1193742	231	1.61
1994	7	3738	653445	2855	8,485,086	1198924	236	1.62
1998	7	3244	565250	3063	10,987,665	1298317	233	1.67
1968	8	10538	2595497	10289	24,290,318	3487842	235	1.39
1972	8	11675	2683044	11157	28,019,981	3706856	237	1.51
1976	8	11605	2256582	11380	19,856,397	3276429	229	1.46
1982	8	9192	1400906	8012	12,161,543	1978858	188	1.48
1985	8	10170	1982916	8906	19,149,638	3201248	234	1.64
1988	8	9898	2154885	9345	23,761,036	3487983	242	1.61
1992	8	5479	994962	6561	11,187,642	1789145	241	1.64
1994	8	5652	1030619	6598	13,369,826	1889127	250	1.46
1998	8	5537	1117241	5626	17,873,598	2111968	231	1.44
1968	9	4164	1477728	6751	13,418,449	1859064	237	1.47
1972	9	4885	1611343	7701	14,859,287	1841115	234	1.60

Year	Region	Capacity	Sawlogs	SIC 242 Employment	Other	Lumber	Operating Days	Shifts
1976	9	5199	1554018	8009	10,259,863	1705760	239	1.56
1982	9	4833	1086557	5850	9,144,749	1311021	194	1.61
1985	9	6029	1389785	5695	11,371,963	1663706	227	1.55
1988	9	5703	1323401	6127	11,693,571	1697720	234	1.66
1992	9	2328	628547	4528	7,207,393	803804	256	1.85
1994	9	2632	574156	3563	8,918,298	835609	235	1.59
1998	9	1895	500194	2721	7,404,691	753476	239	1.68