Productivity in the U.S. and Canadian sawmill industries: A nonparametric programming analysis

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Abstract

In this study, we use a nonparametric programming approach to estimate technical efficiency and total factor productivity (TFP) growth of sawmill industries in various regions of the United States and Canada between 1963 and 2001. The results show that while the Canadian sawmill industry was more efficient, the U.S. sawmill industry had higher productivity growth rates. Technical efficiency and TFP growth varied among regions, and all regions except the U.S. West moved toward the industry frontier over time. Assumption of Hicks neutrality in production is rejected, and a widening gap between TFP growth rates of sawmill industries in these two countries since early 1990s is observed.

Productivity measures the efficiency with which inputs are transformed into outputs. Higher productivity occurs when larger quantities of outputs are produced with given inputs. Among various techniques being used to assess the performance of industries, total factor productivity (TFP), the ratio of an index of aggregate output to an index of aggregate input, provides a simple yet comprehensive measurement.

Productivity in the North American sawmill industries plays an important role in resource allocation and relative competitiveness among regional counterparts. Although costs of inputs affect relative competitiveness in the short run, competitiveness in the long run is determined by productivity growth. Previous studies on the productivity growth of the U.S. and Canadian sawmill industries produced some mixed results. A few studies suggest that there was little or no technical progress in Canada, and productivity growth in the Canadian sawmill industry was lower than the U.S. counterpart (Constantino and Haley 1989, Ghebremichael et al. 1990, Abt et al. 1994, Nagubadi and Zhang 2006). At one extreme, Meil and Nautiyal (1988) report negative TFP growth for all sawmill industries in four Canadian regions between 1950 and 1983. On the other hand, Gu and Ho (2000) estimate that TFP growth of lumber and wood products industry increased annually by 0.62 percent in Canada but decreased by 0.21 percent in the United States between 1961 and 1995.

Often, an index approach or an econometric model is used to estimate productivity growth. Both approaches assume that all firms in the industry operate efficiently, which may not be the case in the reality, and some specific forms of cost or profit functions are assumed for econometric analysis. This study attempts to expand the analytic scope of the technical efficiency and productivity of the sawmill industry in North America. It differs from previous studies in North America in two aspects: First, it uses the nonparametric programming approach, which is more flexible and has been used in the area of agricultural and industrial productivity analysis (e.g., Granderson and Linvill 1997, Preckel et al. 1997, Arnade 1998, Yin 1998, 1999, 2000; Hailu and Veeman 2001, Nin et al. 2003, Umetsu et al. 2003). Second, it looks into the technical efficiency and productivity growth of the sawmill industry at state/provincial as well as regional levels. The results may shed some light on the evolution of sawmill industry productivity by productivity components on a disaggregated level.

The nonparametric programming approach is also known as Data Envelope Analysis (DEA). First introduced by Charnes et al. (1978), it is a data-oriented mathematical programming approach for evaluating the relative performance of a set of peer entities called Decision Making Units (DMUs). With

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DEA, efficient DMUs form the efficient frontier using minimum quantity of inputs to produce the same quantity of outputs. The efficient frontier is the benchmark against which the relative performance of DMUs is measured. The distance of a particular DMU to the efficiency frontier provides a measure of its efficiency.

The nonparametric programming approach (Färe et al. 1994) involves estimating a Malmquist index based on input or output (Caves et al. 1982). Compared to other methods, this approach has the advantage of imposing no *a priori* restrictions on the functional form of the underlying technology and allowing for inefficiency in production (Varian 1984). This approach is also capable of decomposing productivity growth into changes in technical efficiency over time and shifts in technology over time. Although it is already extensively applied in many area of economics, its use in sawmill productivity analysis remain limited (Nyrud and Baardsen 2003).

The next section reviews the nonparametric Malmquist productivity index, followed by the application of the method to the sawmill industry in the United States and Canada. The remaining sections present the results, conclusions and discussion.

Methodology: distance function and Malmquist Productivity Index

Suppose that for each time period $t = 1, \ldots, T$, the feasible production set of the industry is

$$S^t = \{(\mathbf{x}^t, \mathbf{y}^t): \quad \mathbf{x}^t \text{ can produce } \mathbf{y}^t\} \qquad [1]$$

where $\mathbf{x}^t \in R_+^N$ and $\mathbf{y}^t \in R_+^M$ are input and output quantity vectors from N and M dimensional real number spaces; and N and M are the total number of inputs and outputs. S^t is assumed to be closed, bounded, convex and satisfies strong disposability[1] of outputs and inputs. Following Shephard (1970), output-based distance function at t is defined as the reciprocal of maximum proportional expansion of output vector $\mathbf{y}^t$ given input $\mathbf{x}^t$:

$$D_0^t(\mathbf{x}^t, \mathbf{y}^t) = \inf\left\{\theta: \left(\mathbf{x}^t, \frac{\mathbf{y}^t}{\theta}\right) \in S^t\right\} = (\sup\{\theta: (\mathbf{x}^t, \theta\mathbf{y}^t) \in S^t\})^{-1}. \qquad [2]$$

$D_0^t(\mathbf{x}^t, \mathbf{y}^t)$ can be obtained by solving the following linear programming model:

$$\underset{\lambda_k, \theta_{k*}}{\text{Maximize}} (D_0^t(\mathbf{x}^t, \mathbf{y}^t))^{-1} = \theta_{k*}^t. \qquad [3]$$

Subject to:

$$\sum_{k=1}^{K} \lambda_k \mathbf{y}_{km}^t \geq \mathbf{y}_{k*m}^t \theta_{k*}^t, \quad m = 1, \ldots, M, \quad k = 1, \ldots, K$$

$$\sum_{k=1}^{K} \lambda_k \mathbf{x}_{kn}^t \leq \mathbf{x}_{k*n}^t, \quad n = 1, \ldots, N, \quad k = 1, \ldots, K$$

$$\lambda_k \geq 0, \quad k = 1, \ldots, K,$$

where m indexes outputs; n indexes inputs; k indexes DMUs (k^* is a particular region of interest); λ_k is weight on DMU k; θ_{k*}^t is efficiency index, or reciprocal of distance function for region k^* at t. Inequalities for inputs and outputs make free disposability possible. Non-negativity of λ_k allows the model to exhibit constant returns to scale. In the same way, the distance from DMUs in time period t relative to the frontier in $t + 1$ can be defined as $D_0^{t+1}(\mathbf{x}^t, \mathbf{y}^t)$.

Distance function equals 1 when the DMU of interest is on the frontier, or technically efficient, and less than 1 when its production is technically inefficient. The greater the distance function is, the closer the decision making unit is to the efficient production frontier. The distance function provides a complete characterization of production technology.

Productivity change of a sawmill industry over time can be estimated by Malmquist productivity index, developed based on the distance functions. Two simple Malmquist indices can be defined based on technology reference of time periods. Using the technology at t as reference, the period t-based Malmquist index is defined as

$$M_0^t = \frac{D_0^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_0^t(\mathbf{x}^t, \mathbf{y}^t)}. \qquad [4]$$

Using the technology at $t + 1$ as reference, the period $t + 1$-based Malmquist index is

$$M_0^{t+1} = \frac{D_0^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_0^{t+1}(\mathbf{x}^t, \mathbf{y}^t)}. \qquad [5]$$

A Malmquist index of greater than 1 (less than 1) implies technical progress (technical regress). As Färe et al. (1997) note, however, these two measures may not provide consistent results in some cases. Following Caves et al. (1982), Färe et al. (1994) suggest to use geometric mean of M_0^t and M_0^{t+1} as the output-based Malmquist index (M_0), which is

$$M_0 = [M_0^t \times M_0^{t+1}]^{\frac{1}{2}} = \left[\frac{D_0^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_0^t(\mathbf{x}^t, \mathbf{y}^t)} \times \frac{D_0^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_0^{t+1}(\mathbf{x}^t, \mathbf{y}^t)}\right]^{\frac{1}{2}}. \qquad [6]$$

Furthermore, Färe et al. (1994) show that M_0 can be decomposed into an efficiency change component and a technical change component. Thus, Eq. [6] is equivalent to:

$$M_0 = \frac{D_0^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_0^t(\mathbf{x}^t, \mathbf{y}^t)} \times \left[\frac{D_0^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_0^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})} \times \frac{D_0^t(\mathbf{x}^t, \mathbf{y}^t)}{D_0^{t+1}(\mathbf{x}^t, \mathbf{y}^t)}\right]^{\frac{1}{2}}. \qquad [7]$$

where the first part on the right hand side of the equation is defined as efficiency change (*EFFCH*) or "catch up", which measures the change in how far the observed decision making unit is from the potential production frontier between period t and period $t + 1$. The second part is defined as technical change (*TECH*) or "innovation", which captures the shift in technology between two periods. In **Figure 1**, the *EFFCH* is $\frac{OA^{t+1}}{OP^{t+1}} \Big/ \frac{OA^t}{OP^t}$, and the *TECH* is $\frac{OP^{t+1}}{Of} \Big/ \frac{Oe}{OP^t}$ for unit A.

Nin, Arndt, and Preckel (2003) show that these three Malmquist indices (M_0^t, M_0^{t+1}, and M_0) have the same efficiency change. Potential difference stems from estimates of technical change. When technical change is biased (either input or output biased), estimates of technical change from these three indices will be different. Färe et al. (1997) decompose the technical change component of M_0 into three parts: output-biased technical change (*OBTECH*), input-biased technical

[1] Which means if $(\mathbf{x}^t, \mathbf{y}^t) \in S^t$, then $(\tilde{\mathbf{x}}^t, \tilde{\mathbf{y}}^t) \in S^t$ for all $(\tilde{\mathbf{x}}^t, \tilde{\mathbf{y}}^t)$ such that $\tilde{\mathbf{x}}^t \geq \mathbf{x}^t$ and $\tilde{\mathbf{y}}^t \geq \mathbf{y}^t$.

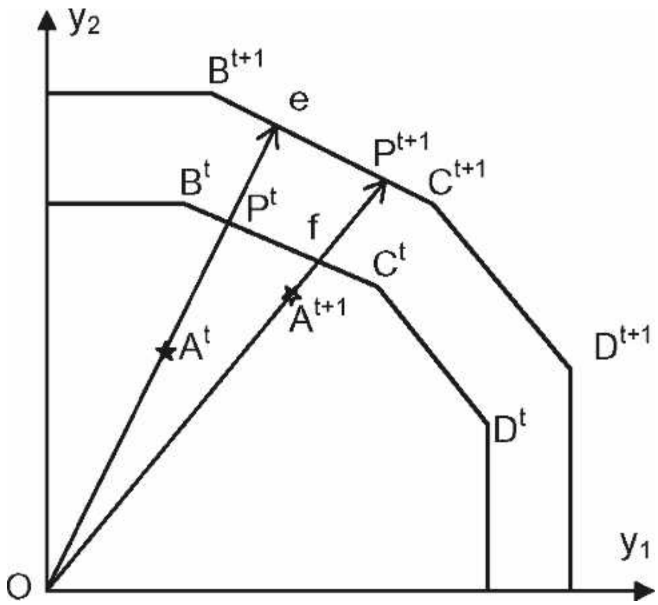

Figure 1. — Output possibility sets, period t and t + 1.

change (*IBTECH*), and the magnitude of technical change under input and output neutrality (*MATECH*):

$$TECH = \underbrace{\left[\frac{D_0^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_0^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})} \Bigg/ \frac{D_0^t(\mathbf{x}^{t+1}, \mathbf{y}^t)}{D_0^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^t)} \right]^{\frac{1}{2}}}_{OBTECH} \times \underbrace{\left[\frac{D_0^t(\mathbf{x}^{t+1}, \mathbf{y}^t)}{D_0^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^t)} \Bigg/ \frac{D_0^t(\mathbf{x}^t, \mathbf{y}^t)}{D_0^{t+1}(\mathbf{x}^t, \mathbf{y}^t)} \right]^{\frac{1}{2}}}_{IBTECH} \times \underbrace{\frac{D_0^t(\mathbf{x}^t, \mathbf{y}^t)}{D_0^{t+1}(\mathbf{x}^t, \mathbf{y}^t)}}_{MATECH}. \quad [8]$$

Note that this decomposition is valid only under the assumption of constant returns to scale (Färe et al. 1997). *OBTECH* measures the output bias of technical change by the ratio of the magnitude of technical change along a ray through $\mathbf{y}^{t+1}$ to the magnitude of technical change along a ray through $\mathbf{y}^t$ holding input vector fixed at $\mathbf{x}^{t+1}$. *IBTECH* captures the input bias of technical change by providing the ratio of the magnitude of technical change along a ray through $\mathbf{x}^{t+1}$ to the magnitude of technical change along a ray through $\mathbf{x}^t$ holding output vector fixed at $\mathbf{y}^t$. *MATECH* measures the magnitude of technical change along a ray through period *t*. *OBTECH* = 1 implies neutral output technical change, and *IBTECH* = 1 is associated with neutral input technical change.

Figure 1 illustrates the case of two outputs (y_1 and y_2). The frontier at *t* is developed by DMU *B*, *C*, and *D*. For DMU *A*, the distance function is $\frac{OA^t}{OP^t}$ at *t* and $\frac{OA^{t+1}}{OP^{t+1}}$ at *t* + 1. The distance function of DMU A from the production point in *t* relative to the frontier in *t* + 1 is $\frac{OA^t}{Oe}$. Consequently, M_0^t is $\frac{OA^{t+1}}{Of} \Big/ \frac{OA^t}{OP^t}$ and M_0^{t+1} is $\frac{OA^{t+1}}{OP^{t+1}} \Big/ \frac{OA^t}{Oe}$.

The nonparametric programming approach, however, is criticized by some researchers for sensitivity of its results to outliers and lack of pursuant power in statistics (Koop et al. 1999). Most of previous studies (Granderson and Linvill 1997, Preckel et al. 1997, Arnade 1998) using this approach assume that the observed frontier is the true frontier (not just an estimate) and distance functions are deterministic; thus the results may vary substantially if the outliers are not present. As Simar and Wilson (2000) note, if the observed data are viewed as generated from the true production set, then estimates of efficiency from the frontier model are subject to uncertainty due to sampling variation.

As a remedy, a bootstrapping approach is used in this study to provide statistical inference of the estimates. Bootstrapping procedure is currently the most popular method to estimate confidence intervals for distance functions (and Malmquist productivity indices) (e.g., Simar and Wilson 1998, 1999, 2000; Henderson and Zelenyuk 2004).

Bootstrapping generates an appropriately large number of pseudo samples from the feasible production set

$$S^* = \{(\mathbf{x}_{lt}^*, \mathbf{y}_{lt}^*) | \quad l = 1, \ldots, L; \quad t = 1, 2\} \qquad [9]$$

where *L* is the size of the pseudo samples, and *l* is the index of elements in it. For each bootstrapping replication, Eq. [**3**] is used to estimate the distance function for each observation in the original sample to the frontier formed by the pseudo samples.[2] Consequently, Malmquist indices, Färe productivity indices, and their components are obtained based on the distance functions described in Eqs. [**4**] to [**7**]. R[3] and two other software packages are used for simulation. One of them is FEAR developed by Wilson (2005) for Data Envelopment Analysis, the other is BOOT developed by Canty (2002) for bootstrapping. Since FEAR only deals with sensitivity analysis of a single time period distance function, a R-program is created by the authors in this study to do bootstrapping for indices based on multiple time periods. Replication of bootstrapping is set to 1000. Confidence intervals for the indices are obtained by applying a normal approximation method to the bootstrapping results. The index is significantly different from unity (indicating no change in productivity or efficiency) if the interval does not include unity.

Data

Sawmill industries are covered in the 1987 Standard Industry Classification (SIC) Code 242 for the U.S. and 251 for Canada. In 1997, a new industry classification system, the North American Industry Classification System (NAICS) replaced the SIC system. According to Nagubadi and Zhang (2006), a bridge between SIC and NAICS is constructed based on value of shipments, number of employees, and annual payrolls in 1997. All principal production data in NAICS are then converted. Canadian series are merged using average proportions developed from data reported for the same years 1990 to 1997 under NAICS and SIC classifications.

Our data cover 1963 to 2001 for 26 U.S. states and 8 Canadian provinces.[4] In 2001, the 26 states accounted for 96.8 per-

[2] See Davison and Hinkley (1997) for more on bootstrapping.

[3] R is a language and environment for statistical computing and graphics.

[4] Selected U.S. western states are California (CA), Idaho (ID), Montana (MT), Oregon (OR), Washington (WA). Selected U.S. northern states include Indiana (IN), Maine (ME), Michigan (MI), Missouri (MO), New York (NY), Ohio (OH), Pennsylvania (PA), Wisconsin (WI), West Virginia (WV). Selected U.S. southern states cover Alabama (AL), Arkansas (AR), Florida (FL), Georgia (GA), Kentucky (KY), Louisiana (LA), Mississippi (MS), North Carolina (NC), South Carolina (SC), Tennessee (TN), Texas (TX), and Virginia (VA). The Canadian provinces covered in this study are Alberta (AB), British Columbia (BC), Manitoba (MB), New Brunswick (NB), Nova Scotia (NS), Ontario (ON), Quebec (QC), and Saskatchewan (SK).

cent of softwood lumber production and 93.2 percent of hardwood lumber production in the United States, while the 8 provinces accounted for about 99 percent of Canadian softwood and hardwood lumber production. Since state-level lumber production data prior to 1963 are not available, our study period covers 1963 to 2001. All sawmills in each state or province were collectively treated as a comparable DMU. For purpose of regional comparison, selected states of the United States are classified into three regions: West, South, and North. Canadian provinces are classified into British Columbia, Ontario, Quebec, and Others.

Our main data sources for the U.S. industry are Annual Survey of Manufactures (ASM), and Census of Manufacturing (CM) from the U.S. Bureau of Census (various years). Data for the Canadian industry are from Annual Census of Manufactures (ACM) and the CANSIM II (Statistics Canada, various years), and Canadian Forest Service. Five main inputs (production labor, non-production labor, capital, energy, and wood materials) and three main outputs (softwood lumber, hardwood lumber, and wood chips) are used. A detailed description of the inputs and outputs data are presented in the appendix.

Results

The non-parametric programming method is applied to the time-series dataset above to construct cross sectional best-practice frontiers year by year. Outputs or inputs from different states/provinces under the same category are assumed to be homogeneous. Technology is assumed to be constant returns to scale for the Malmquist index estimation and further decompositions.

Distance function and technical efficiency

As the measure of technical efficiency, distance functions are calculated for each state/province every year. Over the 39 years, some states/provinces stayed on the efficient frontier more often than others, especially for British Columbia and Saskatchewan in Canada and Idaho, Montana, Oregon, and West Virginia in the United States (80% or more of time). Among them, Oregon is the only state that remained on the frontier during the whole period. Other states/provinces, mostly in the U.S. South, were on the frontier for less than 20 percent of time. North Carolina was the only state that had been on the frontier for less than 5 percent of the time.

Weighted arithmetic means (WAM)[5] of percentage of time for each region and country on the efficient frontier are calculated. The Canadian sawmill industry was shown more efficient. During 1963 to 2001, Canadian sawmills stayed on the industry frontier 74 percent of time while American sawmills stayed on the frontier 56 percent of time; the U.S. West (81% of the time) and the North (47%) were more likely to be on the frontier than the U.S. South (30%).

Considering the softwood lumber trade dispute between the two countries, the whole period is divided into three roughly equal subperiods: 1963 to 1972, 1973 to 1986, and 1987 to 2001. Free trade largely prevailed in the first two subperiods.

Table 1. — Percentage of time on the industry frontier over different periods.

Province/State	1963 to 1972	1973 to 1986	1987 to 2001	1963 to 2001
Canada:	76	86	67	74
British Columbia	90	100	67	85
Ontario	10	79	87	64
Quebec	50	50	60	54
Others	64	73	69	65
Alberta	50	64	93	72
Manitoba	100	79	60	77
New Brunswick	100	100	40	77
Nova Scotia	20	29	0	15
Saskatchewan	90	79	87	85
United States:	52	63	60	56
North	55	45	46	47
Indiana	20	93	60	62
Maine	20	21	73	41
Michigan	90	29	53	54
Missouri	60	21	47	41
New York	30	36	27	31
Ohio	50	29	27	33
Pennsylvania	60	29	0	26
Wisconsin	60	50	27	44
West Virginia	70	100	100	92
South	27	18	45	30
Alabama	0	14	60	28
Arkansas	10	7	27	15
Florida	40	50	87	62
Georgia	80	7	53	44
Kentucky	100	71	73	79
Louisiana	30	14	67	38
Mississippi	10	36	53	36
North Carolina	0	0	7	3
South Carolina	50	14	53	38
Tennessee	30	36	7	23
Texas	0	7	33	15
Virginia	40	21	53	38
West	65	95	79	81
California	30	100	33	56
Idaho	100	93	100	97
Montana	80	100	100	95
Oregon	100	100	100	100
Washington	20	79	60	56

The third subperiod covered various managed trade arrangements in export tax, tariff-rated quota, and import duties on Canadian softwood lumber exports to the United States. The classification may help us relate trade actions and these two countries' sawmill productivity.

Table 1 presents the WAM percentage of time on the industry-wide frontier for each state/province for 1963 to 2001 and three subperiods.[6] Some states/provinces (e.g., British Columbia, Manitoba, and New Brunswick in Canada, and Georgia, Michigan, Pennsylvania, and Wisconsin in the U.S.)

[5] Since each state/province has different share in lumber production, weighted average is a better estimate for regional and national productivity growth than simple average. See Färe and Zelenyuk (2003) for detailed discussion on it. Volume of lumber production (sum of softwood and hardwood) is used as the weight in this study.

[6] Distance functions by years are available from the authors upon request.

were efficient during the first two periods but not in the latest period. Some others (e.g., Alberta and Ontario in Canada, and Alabama, Florida, Indiana, Louisiana, Maine, Mississippi, Texas, and Washington in the U.S.) were often off the efficient frontier in the early periods but their performance gradually improved in the last period. In the latest subperiod, Alberta as well as Idaho, Montana, Oregon, and West Virginia formed the "best practice" frontier. Although most other western states remained on the frontier, California apparently moved off from the frontier after the late 1980s.

For most Canadian provinces, 1973 to 1986 was a period associated with the highest concurrency rate of being technical efficient. On the other hand, 1987 to 2001 was a period during which most of Canadian provinces moved off the industry frontier, especially for British Columbia and Quebec, the largest two softwood production provinces in Canada. Apparently, restrictions on exports of Canadian softwood lumber might affect the efficiency of Canadian sawmills.

Färe Malmquist productivity index and components

Table 2 provides a summary of the Färe productivity growth index and its decomposition into efficiency and technical changes for each region and country. From 1964 to 2001, the weighted annual productivity growth of the U.S. sawmill industry was 2.5 percent while that for the Canadian sawmill industry was 1.3 percent. All U.S. states except for Michigan experienced comparable productivity growth. Most Canadian provinces experienced progress during the study period, Quebec being an exception.

Difference in productivity growth is mainly attributable to the difference in technical change for Canada and the United States during the whole study period (1.2% for Canada and 2.4 percent for the U.S.). Most regions except the U.S. West had positive efficiency change, indicating a trend of moving toward the industry efficient frontier. Regress in technical change contributed to the regress in productivity growth for Quebec.

Similar to that of distance function (efficiency score), sawmill productivity growth rate also varied over the subperiods for both countries and all regions.[7] During the first period, Canada and the United States possessed comparable TFP growth rate (3.2% for Canada and 3.4 percent for the U.S annually). However, the United States grew at a higher rate than Canada in the later periods. The U.S. North possessed the highest growth rate in the first subperiod. The productivity growth for sawmill industries in British Columbia, Quebec, and Ontario, the largest three Canadian softwood lumber producing provinces, slowed down in the last sub period. On the other hand, TFP of sawmill industries in provinces that were not subjected to trade actions (Nova Scotia and New Brunswick) grew at a higher rate.

Figure 2 shows the trend in annual Färe TFP growth indices for the U.S. and Canadian sawmill industries from 1964 to 2001. Generally, variation in the TFP growth rate for the Canadian sawmill industry was relatively small until the mid1980s. For the U.S., the TFP growth rate was the most variant during the 1970s and early 1980s.

[7] Färe TFP growth indices for each state/province, region, and country in various time periods are available from the authors.

Table 2. — Färe productivity index, efficiency change, and technical change for 1964 to 2001.

Province/State	Färe index (M_0)	Efficiency change (EFFCH)	Technical change (TECH)
Canada:	1.013	1.001	1.012
British Columbia	1.014	1.001	1.012
Ontario	1.016	1.002	1.016
Quebec	0.996	1.001	0.999
Others	1.028	1.004	1.025
Alberta	1.051	1.001	1.048
Manitoba	1.004	0.990	1.009
New Brunswick	1.009	0.999	1.009
Nova Scotia	1.013	1.022	1.005
Saskatchewan	1.024	1.002	1.020
United States:	1.025	1.001	1.024
North	1.026	1.000	1.027
Indiana	1.009	0.988	1.018
Maine	1.037	1.011	1.027
Michigan	0.996	1.000	0.998
Missouri	1.024	1.002	1.021
New York	1.055	1.007	1.040
Ohio	1.051	0.993	1.061
Pennsylvania	1.008	0.997	1.013
Wisconsin	1.006	0.994	1.022
West Virginia	1.043	1.004	1.041
South	1.025	1.002	1.022
Alabama	1.026	1.004	1.020
Arkansas	1.035	1.004	1.028
Florida	1.034	1.003	1.030
Georgia	1.009	0.999	1.010
Kentucky	1.050	1.002	1.043
Louisiana	1.027	1.003	1.021
Mississippi	1.021	1.002	1.021
North Carolina	1.032	1.003	1.028
South Carolina	1.029	1.003	1.026
Tennessee	1.040	1.003	1.034
Texas	1.003	0.999	1.006
Virginia	1.021	1.002	1.020
West	1.025	0.999	1.025
California	1.021	0.995	1.028
Idaho	1.023	1.000	1.023
Montana	1.025	1.000	1.024
Oregon	1.030	1.000	1.030
Washington	1.019	1.001	1.017

Figure 3 presents the cumulated Färe TFP growth index for the United States and Canada during the same period using 1963 as the base year. The cumulated index is calculated as sequential multiplicative sums of weighted annual TFP Färe index values. Apparently, the gap in TFP growth between the United States and Canada widened in the late1990s, after Canada had lead the United States in the 1980s.

Bias components of technical change

Technical change is further decomposed into input biased, output biased and neutral components. The results show that *IBTECH* increased by 7.0 percent annually for the U.S., and 5.5 percent for Canada over the 38-year period. *OBTECH* increased by 2.7 percent for the United States and 3.8 percent

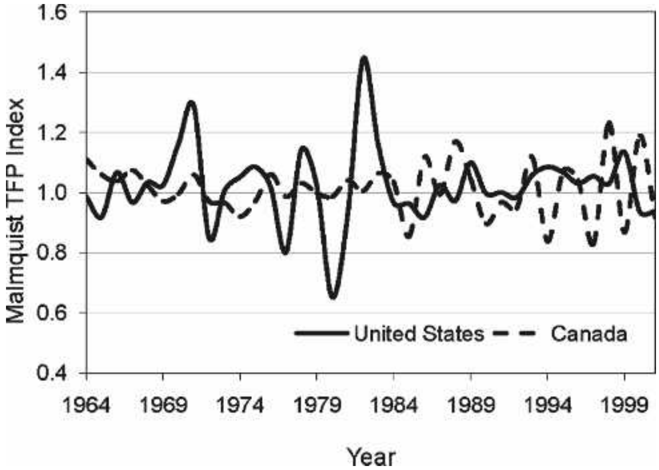

Figure 2. — Annual Färe productivity indices for the U.S. and Canadian sawmill industries, 1964 to 2001.

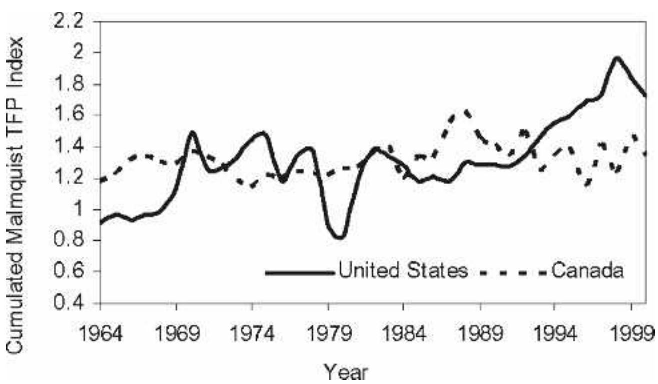

Figure 3. — Cumulated Färe productivity indices for the U.S. and Canadian sawmill industries, 1964 to 2001 (Base = 1963).

for Canada annually. These results suggest that both input and output biased technical change indices were not 1 though it cannot be tested statistically. In other words, sawmill production in the United States and Canada experienced neither Hicks input-neutral nor output-neutral technical change. This indicates that the normal assumption of Hicks neutrality of technical change in traditional TFP growth studies is rejected for both the United States and Canadian sawmill industries. Thus, the traditional treatment of representing the state of technology by a scalar adopted by other studies (e.g., Robinson 1975, Constantino and Haley 1989, Gu and Ho 2000) in TFP growth estimation may yield biased results. Since *IBTECH* is larger than *OBTECH*, technological changes were biased on the inputs side much more than on the outputs side for both countries.

The results of this study are consistent with most previous studies in that both countries experienced progress in TFP. The estimate of annual TFP growth rate for the U.S. sawmill industry is comparable to the findings of Ahn and Abt (2006). The estimate of annual average growth rate of TFP for the Canadian sawmill industry is comparable to the results from Ghebremichael et al. (1990) and Nagubadi and Zhang (2006). Similar to the latter, this study observes a widening gap between the two countries' productivity growth during the later part of the study period.

Sensitivity analysis

The results reported above are based on a method that treats all variables equally. A unit being efficient in lumber production will appear equally efficient to a unit being efficient in its production of chips, even though chips and residues are secondary products with much less value (Nyrud and Baardsen 2003). In most cases, chip value accounts for less than 15 percent of the total output value. A sensitivity analysis is conducted to see the changes in the Färe TFP growth index and its components when only softwood and hardwood are considered in the outputs. The results show that annual productivity growth decreases to 2.0 percent annually for the United States and increases to 1.7 percent for Canada annually. Thus, the general conclusions above stand.

The bootstrapping simulation results[8] show that 69 percent of the Färe TFP growth estimates are significantly different from 1 at the 10 percent level, and 63.4 percent shown significant at the 5 percent level. However, efficiency changes are very sensitive to the selection of the frontier. Only 19.3 percent of the efficiency change estimates are shown to be significant at the 10 percent level. Technical change estimates are better, with 46.75 percent of estimates being significant. The bootstrapping results indicate the estimates of the productivity growth and the technical change indexes are generally reliable, while the estimates of efficiency changes should be interpreted with caution.

The 95 percent confidence interval (CI) of the weighted average of annual Färe TFP growth index for the United States is [1.015, 1.034], and the 95 percent CI for Canada is [1.002, 1.024]. This implies that both countries experienced statistically significant productivity growth during the whole study period (CI does not include 1).

Conclusions and discussion

This study uses a nonparametric programming approach to estimate technical efficiency and TFP growth of the sawmill industries in the United States and Canada. The results show that the Canadian sawmill industry was more likely to be on the industry frontier than the U.S. counterpart. However, because of a higher productivity growth rate, the U.S. sawmill industry nearly caught up with the Canadian industry in technical efficiency in the 1987 to 2001 subperiod. Technical efficiency performance for the selected states and provinces varied with different periods of time.

From 1964 to 2001, the weighted annual productivity growth of sawmill industry for the United States was 2.5 percent while Canadian sawmill industry had a lower growth rate of 1.3 percent. All regions except the U.S. West had a trend of moving toward the industry frontier. Difference in productivity growth was mainly due to the difference in technical change. The technical change associated with sawmill industries in the North America over the 38-year period is not Hicks neutral, and the adoption of traditional neutrality assumption may not be valid in the productivity growth analysis for the U.S. and Canadian sawmill industries.

The policy relevance of this study is three-fold. First, the softwood lumber dispute between the United States and Canada might affect the performance and competitiveness of the sawmill industry differently between countries and among

[8] Bootstrapping results are available from the authors.

regions. Second, this study confirms that there was a widening gap between two countries' productivity growth during the late part of the study period. If this trend continues, the competitive advantage of Canadian sawmill industry may erode. Third, producers in various states or provinces of the two nations could use the results of this study as a reference to judge their competitiveness against their counterparts in other states and provinces.

It should be noted that this study does not consider the quality difference in inputs and outputs across states and provinces. Further, there is difference in output mix in the U.S. and Canadian sawmill industries. The United States has larger proportion of hardwood in total lumber production than Canada. Finally, constant returns to scale is assumed in this study for convenience of the estimation of TFP growth and further decomposition.

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Appendix

Labor Inputs, Energy Input, Softwood and Hardwood Lumber and Wood Chips Outputs

This study uses two types of labor inputs: production labor and non-production labor. Energy input is in trillion *Btu*. See Zhang and Nagubadi (2006) for details on the estimation of lumber outputs, energy cost and price index.

Capital input

Capital stock in 1997 constant U.S. dollars is estimated using the perpetual inventory method (PIM). As in Ahn and Abt (2006), investment on plants and structures is depreciated over 28 years, and machinery and equipment is depreciated over 16 years. Annual capital stock estimates for different asset types are aggregated as a total capital stock for each state/province. Estimate of capital stock for any given state/province s at the end of year t is calculated as:

$$K_{s,t} = \sum_{\tau=0}^{\infty} \phi_\tau I_{s,t-\tau} \quad [\mathbf{A.1}]$$

where τ is age of asset; ϕ_τ is the relative efficiency function at age τ; and I is investment. The hyperbolic efficiency function is:

$$\phi_\tau = \begin{cases} (L-\tau)/(L-\rho\tau) & 0 < \tau < L \\ 0 & \text{otherwise} \end{cases} \quad [\mathbf{A.2}]$$

where L is the service life of asset and ρ is the decay parameter which determines the method of depreciation. Following of the U.S. Department of Labor, Bureau of Labor Statistics (1983), we chose ρ equal to 0.5 for equipment, and 0.75 for structure.

The United States. — We retrieve the end of year investment data on different assets by state from CM and ASM to year 1954. Since PIM requires the investment data since 1935 which are not available, we estimate the investment data of SIC 242 prior to 1954 by using estimates of national non-residential fixed assets by types from the U.S. Department of Commerce, Bureau of Economic Analysis (2005) for SIC 24, the average proportion of capital investment of SIC 242 in SIC 24, and each state's average share in total national capital investment in SIC 242 during 1954 to 1957.

Canada. — Annual capital and repair expenditure data are available for three provinces (Quebec, Ontario, and British Columbia) from 1970 to 2001. Other provinces' investment during the same period is estimated by national sawmill industry flows and stocks of fixed non-residential capital, and each province's average share of national industry added value. For all provinces, capital investment data for 1935 to 1969 are constructed by multiplying national industry fixed capital flows and each province's average share of national industry added value from 1961 to 2001.

Wood inputs

The United States. — Quantities of wood inputs are derived by non-energy material costs and the weighted price of delivered hardwood and softwood sawtimber. See Zhang and Nagubadi (2006) for the estimation of material input quantity.

Canada. — Quantities of wood materials are collected from Statistics Canada, Catalogues 35–204, 35–250, and Catalogue 57–208, for 1963 to1984. Softwood and hardwood sawtimber are treated as homogeneous, and aggregated by volume in terms of MBF, Scribner. For years thereafter, the quantities are estimated by provincial industry materials cost and a price index. The price index is based on the price data of 1963 to 1984 and extended to the following years by using industry raw materials price index from Statistics Canada, CANSIM, Table 330–0006 and catalogue no. 62–011–XPB.