ESTIMATING THE EMPLOYMENT IMPACTS OF TIMBER HARVEST CONSTRAINTS: AN ANALYSIS OF THE DERIVED DEMAND FOR LABOR IN THE SOUTHERN LUMBER SECTOR

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ABSTRACT

Sophisticated derived demand analysis is often used to assess how shifts in timber supply affect the price of raw wood and influence the behavior of firms which purchase wood. How these impacts eventually translate into employment impacts has received less attention. Employment effects have been directly estimated using the assumption of fixed factor shares -- that employment effects will be proportional to timber harvest changes. However, these analyses ignore potential substitution and price effects. In the lumber and wood products sector, the derived demand for labor, with its implications for determining the distribution of regional income and employment impacts, is an influential policy variable worthy of detailed analysis. This study analyzes the derived demand for subaggregates of labor in the southeast region of the United States. It develops an econometric model for evaluating the impacts of changes in timber supply on the demand for labor.

INTRODUCTION

In a recent analysis of timber supply in the United States, the U.S. Forest Service estimated that the nation's timberlands contained 755.935 billion cubic feet of hardwood and softwood "growing stock -- live, sound trees suited for roundwood products." Softwood growing stock comprised 450.881 billion cubic feet or 60 percent of this total. Of the softwood growing stock, 41 percent of this volume was growing under federal ownership on the national
forests, 30 percent was grown by non-industrial, private owners, 16 percent was owned by private forest industry, and 13 percent was controlled by public agencies other than the U.S. Forest Service. Geographically, this volume was distributed with 44 percent growing on the Pacific coast, 23 percent in the south, 22 percent in the Rocky Mountains, and 11 percent in the north (USDA, Forest Service, 1990, pp. 49-50).

A variety of policy factors influence how much of this growing stock is actually available as inventory to the forest products sector for conversion into consumable wood products. In forestry, policy debates center on income and employment impacts of policies which can either positively or negatively affect timber supply. Chief among these are federal subsidy programs, state forest practice acts, federal timber management policies, and state and federal environmental policies such as those affecting wetlands and the habitat of endangered and threatened wildlife. Most hotly debated at present are policies for wildlife habitat preservation - such as the Northern Spotted Owl in the northwest, and the Red-Cockaded Woodpecker in the southeast -- which either have reduced or have the potential to reduce the inventory of available stumpage from public and private lands, and affect dependent communities. The recent timber summit illustrated that the employment and income consequences of these policy decisions are the primary variables of interest (Office of the President, 1993). Other events, such as adverse weather and insect infestations also affect stumpage supply and have similar impacts on dependent communities.

At the industry level, most previous modeling efforts have been directed toward estimating the price effects that these circumstances induce in timber markets. How these circumstances translate eventually into employment impacts has only been broadly analyzed. Sample and LeMaster (1992) examined four studies on the economic impacts resulting from the protection of the northern spotted owl in the Pacific northwest. All four studies (Anderson and Olson, 1991, Beuter, 1990, Gordon et al., 1991, and USDA, Forest Service, 1991) utilized a naive approach to projecting employment responses to decreases in timber supply.

[In these four studies,] [e]mployment levels are projected by estimating the number of jobs at a given timber harvest level, which is then extrapolated to project changes in employment associated with timber harvesting and processing (Sample and LeMaster, 1992, p. 33).

Thus, the primary method for addressing employment has been the assumption of fixed factor shares -- that employment effects will be proportional to timber harvest changes. These employment projections are usually followed up by an input-output analysis which yields estimates of the total impact of these employment effects on specific regions.

Industry studies have produced evidence, however, that the implicit fixed factor production assumption is incorrect (Abt, 1984, 1987, Stier, 1980), and that wood and labor are substitutes in the lumber industry. These derived demand studies have generally concentrated on the substitution between timber and aggregated labor, capital, and technical change. Labor has been treated as a homogeneous input.

These occupational attributes are also economic attributes. The firm’s decision as to the mix of labor to use in its operation is an economic one based in large measure upon the differing skills and productivity potential that these attributes present in its workforce. In theory, it should be possible to apply economic analysis to examine how firms utilize these categories of labor in combination with other production factors. Other things being equal, the analysis of past performance in the utilization of various types of labor, and its mix with other production factors, should indicate future trends in how these various types of labor will be utilized.
Some work has been done in disaggregating factor inputs according to quality measures. This includes one study which disaggregated labor in the forest products sector to estimate each labor category's elasticity of substitution with capital (Weiss, 1977). That study aggregated U.S. data for the furniture, lumber, and wood products industry and did not include timber and its derived demand.

Therefore, the question remains as to whether it is consistent to treat labor as a homogeneous input. So far, there has not been an examination of the differential effects on disaggregated classes of labor, such as production and non-production labor with wood, based upon derived demand techniques in the lumber industry. Such an examination would provide useful policy insights. If there are differential effects, then the income differences between labor types imply that the income effect may be significantly different than that implied by an aggregate labor analysis. Gains (losses) to the broadly defined labor category may conceal losses (gains) to certain labor groups within the category. For example, management employees in the lumber sector may be affected differently than production employees when production is curtailed. Production employees may be less educated and of lower income than management employees. Therefore it is not only possible that a reduction in the generally described "labor" factor can consist of different impacts on different labor groups, but it may actually more severely affect those most often targeted by employment policies -- and least able to adjust -- than the general effect would indicate. These are important considerations in dealing with welfare, distribution, and community stability and income issues. Thus, the derived demand for labor, with its implications for determining the distribution of regional income and employment impacts, is a more influential policy variable than the derived demand for other factors. This paper uses a derived demand model to explore whether differences exist in the derived demand for production and non-production labor in the Southeast. It then applies this specification to model the employment and income consequences of timber price changes.

METHODS

Production factors used by the lumber industry possess distinctive attributes which determined which of the available methods to apply for the analysis. Labor and wood factors were assumed to vary in the short run, subject to a given level of capital stock and output. Since labor -- a variable factor -- was the focus of the study, a variable cost function was used. Data were gathered to satisfy the requirements of this function.

Data Sources

The functional specification used in this study required time series data on capital stock, material use and prices, labor use and wages, and output quantities. Because a variable cost function was used, capital and output price information were not required in the function. However, data on capital and output prices were required in order to produce Törnqvist indices of capital and output quantities used in the functional specification. Aggregated data for these characteristics were obtained from an existing data base, once used in a regional total factor
productivity study done by Abt et al. (1994). It was originally extracted from the Department of Commerce's "Census of Manufacturers" and "Annual Survey of Manufacturers," both of which provide detailed information by industry.

Information on the standard industrial classification (SIC) 242, sawmills and planing mills, was used to describe the lumber industry in Alabama, Georgia, and Mississippi. These states were chosen based upon similarities in the price and product of their lumber sectors and the availability of historical data. The data series began in 1964 and ended in 1988. During several years where SIC 242 data were not available, estimates were calculated based upon interpolation of SIC 24 trends. For the present study, the data was disaggregated into the three states studied to increase the number of observations and the degrees of freedom in the sample.

The labor component was also disaggregated into two occupational classifications -- production, or blue-collar (B), and non-production, or management (M).

Theoretical Framework

Assuming the firm minimizes its costs for an exogenously specified level of production, a total cost function dual to the primal production function can be derived (Shephard, 1953):

\[ TC = g(P_w, P_B, P_M, P_K, Y, t) \]

where
- \( TC \) = Total Cost
- \( P_w \) = Price of wood
- \( P_B \) = Price of production (blue-collar) labor
- \( P_M \) = Price of non-production (management) labor
- \( P_K \) = Price of capital
- \( Y \) = Output
- \( t \) = Time as a proxy for state of technology

From the total cost dual, a variable cost function can be derived. In the short run, the firm minimizes its variable costs for an exogenously determined level of output, a given state of technology, and given levels of inputs such as capital which are fixed in the short run.

\[ VC = g(P_w, P_B, P_M | K, Y, t) \]

where
- \( VC \) = Variable Cost = \( P_w W + P_B B + P_M M \)

Cost minimization through the Lagrangian approach requires prior knowledge of the form of the production function because it must operate as the Lagrangian constraint. The advantage of using a dual cost function is demonstrated in the ability to compute cost minimizing factor quantities without any knowledge of the form of the production function. Shephard's lemma asserts that the solution to deriving the cost minimizing demand for factor \( i \) can be found simply through the partial differentiation of the variable cost function:

\[ \frac{\partial VC}{\partial P_i} = X_i(P_w, P_B, P_M | K, Y, t) \]
where

\[ X_i = W, B, M \]
\[ P_i = P_w, P_B, P_M \]
\[ X_i(P_w, P_B, P_M | K, Y, t) = \text{the cost minimizing variable factor demand function.} \]

To establish whether the \( i \)th and \( j \)th inputs are substitutes or complements with each other requires the estimation of the cross-price elasticities:

\[ \varepsilon_{ij} = \frac{\partial i}{\partial P_j} \cdot \frac{P_j}{i} \]

With this estimate, it is then possible to calculate the Allen partial elasticities of substitution between inputs \( i \) and \( j \):

\[ \sigma_{ij} = \frac{\varepsilon_{ij}}{S_j} \]

Inputs \( i \) and \( j \) are substitutes when \( \sigma_{ij} > 0 \) and complements when \( \sigma_{ij} < 0 \).

**Empirical Estimation**

The translog cost function is the main functional form used in applying duality theory to production analysis. Its advantages derive from its intrinsic flexibility, well documented in the literature (Berndt, 1991, pp. 469-486). For output \( Y \), fixed inputs \( K \) and \( t \), variable input \( W \) and heterogeneous variable labor inputs \( B \) and \( M \), the translog variable cost function assumes the form:

\[ \ln VC = \ln \alpha_0 + \alpha_Y \ln Y + \alpha_w \ln P_w + \alpha_K \ln K + \alpha_t t + \alpha_M \ln P_M + \alpha_B \ln P_B \]

\[ + \frac{1}{2} \left[ \alpha_{YY} (\ln Y)^2 + \alpha_{WW} (\ln P_w)^2 + \alpha_{KK} (\ln K)^2 + \alpha_{tt} t^2 + \alpha_{MM} (\ln P_M)^2 + \alpha_{BB} (\ln P_B)^2 \right] \]

\[ + \alpha_{YW} (\ln Y) (\ln P_w) + \alpha_{WK} (\ln Y) (\ln K) + \alpha_{YM} (\ln Y) (\ln P_M) + \alpha_{YB} (\ln Y) (\ln P_B) \]

\[ + \alpha_{WK} (\ln P_w) (\ln K) + \alpha_{WM} (\ln P_w) (\ln P_M) + \alpha_{WB} (\ln P_w) (\ln P_B) \]

\[ + \alpha_{KK} (\ln K) (\ln P_M) + \alpha_{KB} (\ln K) (\ln P_B) \]

\[ + \alpha_{MM} (\ln P_M) (\ln P_B) \]

\[ + \alpha_{WB} (\ln Y) t + \alpha_{wt} (\ln P_w) t + \alpha_{Kt} (\ln K) t + \alpha_{Mt} (\ln P_M) t + \alpha_{Bt} (\ln P_B) t \]

where \( Y, W, B, M, K, \) and \( t \) are as previously defined.

The conditions which must be satisfied for this cost function to be well-behaved are:
\[ \sum_{i=1}^{n} \alpha_i = 1 \]
and
\[ \sum_{i=1}^{n} \alpha_{ij} = \sum_{j=1}^{n} \alpha_{ji} = \sum_{i=1}^{n} \alpha_{iY} = 0 \]

which imply that the function is homogeneous of degree one (shows constant returns to scale, i.e. it is linearly homogenous) in prices at a given level of \( Y \). The condition required for the function to be homothetic is that \( \alpha_{iY} = 0 \) for all \( i = 1, \ldots, n \).

The logarithmic derivative of Shephard’s lemma applied to the translog variable cost function yields the share of total variable costs that can be imputed to each variable factor:

\[ \frac{\partial \ln(VC)}{\partial \ln(P_i)} = \frac{\partial VC}{\partial P_i} \frac{P_i}{VC} = \frac{P_i X_i}{VC} = S_i \]

where \( S_i \) is the proportion of total variable costs attributable to factor \( i \).

Given the translog variable cost function specified above, the cost minimizing factor share of each variable input can be imputed. For example, the share of variable costs attributable to production labor \( (B) \), management labor \( (M) \), and raw wood \( (w) \) would be, respectively:

\[ \frac{\partial \ln(VC)}{\partial \ln(P_B)} = \frac{P_B B}{VC} = S_B = \alpha_B + \alpha_{BB} (\ln P_B) + \alpha_{BY} (\ln Y) + \alpha_{WB} (\ln P_w) \]

\[ + \alpha_{KB} (\ln K) + \alpha_{MB} \ln P_M + \alpha_{Bt} t \]

\[ \frac{\partial \ln(VC)}{\partial \ln(P_M)} = \frac{P_M M}{VC} = S_M = \alpha_M + \alpha_{MM} (\ln P_M) + \alpha_{YM} (\ln Y) + \alpha_{WM} (\ln P_w) \]

\[ + \alpha_{KM} (\ln K) + \alpha_{MB} (\ln P_B) + \alpha_{Mt} t \]

\[ \frac{\partial \ln(VC)}{\partial \ln(P_w)} = \frac{P_w W}{VC} = S_w = \alpha_w + \alpha_{ww} (\ln P_w) + \alpha_{yw} (\ln Y) + \alpha_{wK} (\ln K) \]

\[ + \alpha_{wM} (\ln P_M) + \alpha_{WB} (\ln P_B) + \alpha_{wt} t \]

Because output quantity \( (Y) \) and the price of wood \( (P_w) \) may be endogenous, the method of instrumental variables was used to predict these two variables in the in the right-hand-sides of the share estimations. Observed output quantity and wood price indices were regressed upon a model which included mortgage interest rates, industrial output, the energy price index, and housing starts for each year. In separate regressions on these instrumental variables, predicted
output quantity and wood price index values had $R^2$ values of 0.94 and 0.92, respectively.

This translog specification produced a total of 21 parameters to estimate, seven in each of the three share equations. The cross-equation symmetry restriction that $\alpha_{ij} = \alpha_{ji}$ reduced the number of free parameters to 18. The number of free parameters was further reduced by imposing homogeneity of degree 1 and homotheticity restrictions on the equations. Homotheticity requires that all $\alpha_{Ir} = 0$ for all $i = 1, \ldots, n$. This reduced the number of free parameters to 15.

The cost shares derived from system of three variable share equations always sum to 1. Therefore, only two share equations were linearly independent. To avoid singularity problems, it was necessary to drop one share equation from the system and use the above identities to indirectly derive the parameters of the third. Berndt (1991, p. 473-474) states that the choice of the share equation dropped should not cause variance in the parameter estimates. For this analysis, the wood share equation was dropped from the system. This reduced the number of free parameters to 11, and the remaining share equation parameters were estimated using the iterative three-stage least-squares (I3SLS) method.

Following Berndt and Hesse (1986), the seven $\alpha_{wj}$ parameters of the dropped wood share equation were indirectly estimated from the directly estimated parameters through the use of the behavioral restrictions mentioned previously. For this model those restrictions were implemented as follows:

\[
\begin{align*}
\alpha_B + \alpha_M + \alpha_W &= 1.0 \\
\alpha_{BB} + \alpha_{BM} + \alpha_{BW} &= 0 \\
\alpha_{BM} + \alpha_{MM} + \alpha_{MW} &= 0 \\
\Rightarrow \alpha_{WW} &= \alpha_{BB} + 2 \alpha_{BM} + \alpha_{MM}
\end{align*}
\]

Note that the cross-equation symmetry restrictions had already set $\alpha_{wm} = \alpha_{MW}$ and $\alpha_{wb} = \alpha_{BW}$.

**RESULTS**

Parameter estimates for the three variable factors appear in table 1. Significance levels of the parameter estimates were generally high, except for the estimate for $\alpha_{ibw}$ which means that any further inferences made with this parameter should be interpreted with caution. However, some immediate preliminary results can be gathered from the parameter estimates as to the bias of technical change with respect to each variable input. If $\alpha_i > 0$, technical change is biased toward input $i$. This means that the technology is "factor $i$ using" over time. If $\alpha_i < 0$, technical change is biased against input $i$. This means that the technology is "factor $i$ saving" over time. The preliminary results show that the technology is biased against both types of
labor, individually, and biased toward wood. This labor bias result refines the existing knowledge of technical change bias in the lumber industry. Vincent et al. (1992) reviewed 23 different forest product industry studies which aggregated labor and found technical change biased against aggregated labor.

Table 1: Parameter Estimates of the Southern Lumber Variable Cost Function

<table>
<thead>
<tr>
<th></th>
<th>Directly (I3SLS) Estimated</th>
<th>Indirectly Estimated</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_B$</td>
<td>0.347 (0.0001)</td>
<td>$\alpha_M$ 0.335 (0.0001) $\alpha_W$ 0.318</td>
</tr>
<tr>
<td>$\alpha_{BM}$</td>
<td>-0.033 (0.0220)</td>
<td>$\alpha_{MM}$ 0.069 (0.0007) $\alpha_{WM}$ $\alpha_{MW}$</td>
</tr>
<tr>
<td>$\alpha_{BW}$</td>
<td>-0.012 (0.6257)</td>
<td>$\alpha_{MW}$ -0.036 (0.0456) $\alpha_{WW}$ 0.049</td>
</tr>
<tr>
<td>$\alpha_{BB}$</td>
<td>0.045 (0.1067)</td>
<td>$\alpha_{MB}$ $\alpha_{BM}$ $\alpha_{WB}$ $\alpha_{BW}$</td>
</tr>
<tr>
<td>$\alpha_{BK}$</td>
<td>-0.073 (0.0001)</td>
<td>$\alpha_{MK}$ 0.060 (0.0009) $\alpha_{WK}$ 0.012</td>
</tr>
<tr>
<td>$\alpha_{BY}$</td>
<td>0</td>
<td>$\alpha_{MY}$ 0 $\alpha_{WT}$ 0</td>
</tr>
<tr>
<td>$\alpha_{Bi}$</td>
<td>-0.002 (0.0043)</td>
<td>$\alpha_{Mi}$ -0.002 (0.0313) $\alpha_{Wi}$ 0.004</td>
</tr>
</tbody>
</table>

* Probability > |t| in parentheses.

Mean values of variable cost shares ($P_i X_i / VC$) over the 25-year period were then calculated for the three variable factors. These values are shown in Table 2.

Table 2: Mean Variable Factor Cost Shares ($S_i$) in the Southern Lumber Sector, 1964-1988

<table>
<thead>
<tr>
<th>Blue-Collar Labor</th>
<th>Management Labor</th>
<th>Wood</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.286</td>
<td>0.348</td>
<td>0.366</td>
</tr>
</tbody>
</table>
Parameter estimates and mean cost share values were then used to estimate Allen substitution elasticities (σ<sub>ij</sub>) and price elasticities (ε<sub>ij</sub>) according to the following formulas:

\[ σ_{ij} = \frac{α_{ij} + S_i S_j}{S_i S_j} \quad \text{where } i ≠ j \]

and

\[ ε_{ij} = \frac{α_{ij} + S_i S_j}{S_i} \quad \text{where } i ≠ j \]

\[ ε_{ii} = \frac{α_{ii} + S_i^2 - S_i}{S_i} \]

As is shown in table 3, the preliminary results indicate that blue-collar labor, management labor, and wood are all substitutes for each other. A one percent increase in the relative price of blue-collar labor and management labor brings about a 0.67 percent increase in their relative quantities. However, there is a higher degree of substitutability between blue-collar labor and wood than management labor and wood. There is also a higher degree of substitutability between blue-collar labor and wood than blue-collar labor and management labor. This is evidence to support the rejection of the fixed factor assumptions.

**Table 3:** Allen Partial Substitution Elasticities (σ<sub>ij</sub>) of the Variable Factors

<table>
<thead>
<tr>
<th></th>
<th>σ&lt;sub&gt;BM&lt;/sub&gt;</th>
<th>σ&lt;sub&gt;BW&lt;/sub&gt;</th>
<th>σ&lt;sub&gt;MW&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.673</td>
<td>0.883</td>
<td>0.714</td>
</tr>
</tbody>
</table>

Table 4 shows the own- and cross-price elasticities for the variable factors in the southern lumber sector. A one percent increase in the price of wood brings about a 0.32 percent increase in the quantity of blue-collar labor and a 0.26 percent increase in the quantity of management labor.

**Table 4:** Price Elasticities (ε<sub>ij</sub>) of the Southern Lumber Sector

<table>
<thead>
<tr>
<th></th>
<th>j=B</th>
<th>j=M</th>
<th>j=W</th>
</tr>
</thead>
<tbody>
<tr>
<td>i=B</td>
<td>-0.557</td>
<td>0.234</td>
<td>0.323</td>
</tr>
<tr>
<td>i=M</td>
<td>0.193</td>
<td>-0.454</td>
<td>0.261</td>
</tr>
<tr>
<td>i=W</td>
<td>0.253</td>
<td>0.248</td>
<td>-0.501</td>
</tr>
</tbody>
</table>
This has interesting short-run implications. First, it shows that, at a given output level, the use of blue-collar and management labor increases as the price of wood increases, although at different rates.

The cross-price elasticities also have implications when considering regional income effects of wood price increases. When combined with relative wages of blue-collar \((P_B)\) and management \((P_M)\) labor, the percentage change in income for each labor group can be estimated for a given percentage change in wood price \((\Delta P_w/P_w)\).

\[
\% \Delta \text{Income}_B = P_B \frac{\Delta B}{B} = P_B \cdot e_{BW} \cdot \frac{\Delta P_w}{P_w}
\]

\[
\% \Delta \text{Income}_M = P_M \frac{\Delta M}{M} = P_M \cdot e_{MW} \cdot \frac{\Delta P_w}{P_w}
\]

The relative wage of management labor averaged 1.63 times the wage of blue-collar labor during the survey period. This means that each one percent increase in the price of wood brings about a 0.43 percent increase in the income of management workers and a 0.32 percent increase in the income of blue-collar workers at a given level of output.

**CONCLUSIONS**

For the three southern states studied, preliminary results show that the demand for labor in the lumber industry is inelastic with respect to wages. However, when the price of wood rises, the use of both management and blue-collar labor rises, holding output constant, although at different rates. For example, the quantity of blue-collar labor increases more for a given wood price increase than management labor. The study shows that the concept of fixed factor proportions can be rejected in the southern lumber industry in that all of the variable factors -- blue-collar and management labor, and raw wood are substitutes for each other. Wood substitutes more for blue-collar labor than for management labor. Technical change is biased against both types of labor, individually, and biased toward the use of wood.

Further research in this area will tie this model in with a timber supply model which estimates wood price changes in response to changing timber inventories. This would complete the link between available timber supply, as affected by policy and environmental factors, and lumber sector employment.

More analysis is planned to compare the results between major timber regions. Labor and technology conditions may vary between, for example, the southern and Pacific northwest regions.

Finally, an interesting area for further research would be to use disaggregated labor income results in a regional input/output model to determine if there is a significant difference in regional multipliers obtained with disaggregated labor.
LITERATURE CITED


