Forest Policy Center

Internal
Working Paper Series
No. 113

Forest Resources, Government Policy, and the Investment Location Decisions of the Forest Products Industry in the Southern U.S.

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Abstract

This paper presents the results of an initial attempt to estimate the effects of state attributes on plant location and investment expenditure of the forest products industry in the southern U.S. A conditional logit model is used to analyze new plant births, and a time-series cross-section model is used to assess the total capital expenditure. Significant positive effects are found for personal income and forest inventory, and negative effects for population density. In the short run, tax and energy costs have negative impacts on new plant births in a state, while in the long run, stumpage price and environmental stringency have negative effects on the capital expenditure. Sensitivity of model specification is documented, and policy implications are discussed.

Keywords: Investment, location decision, forest products industry, conditional logit model, time series cross section model, tax, forest inventory, environmental regulatory stringency.

INTRODUCTION

Industry location has been a subject of great interest to both corporate and government decision-makers. The forest products industry is one of the primary manufacturing sectors in many southern states of the U.S. In Alabama, Louisiana, and Mississippi, for example, the forest industry is one of the largest manufacturing industrial groups in terms of gross state product, total value of shipment, and employment.

The health and competitiveness of the forest industry in a particular state rely on continuous investment. Investment brings new technology, enhances factor endowments, and thus improves the competitiveness of the industry (Porter 1991). More importantly, investment brings employment and economic growth. Therefore, state governments in the South have made great efforts in the last half century to attract forest industry investment to boost their industry production and employment. Various public policies have been used to recruit the industry, including financial incentives such as tax abatements, low property tax, direct state loans, and industrial revenue bonds, and non-financial incentives such as customized industrial training and provision of information to prospects. However, no study can be found that specifically examines the factors influencing the growth in the forest products industry in the southern states.

This study fills in this gap by examining the significance and magnitude of various factors in influencing the growth of the forest products industry in the southern U.S. The availability of microeconomic data at establishment level allows us to apply a conditional logit model (CLM) on the investment location decisions for new forest industry plants. In addition, a time-series cross-section model (TSCS) has been applied to the industry's total investment expenditure. The results show that forest resource endowment, government tax policies, and other socio-economic conditions affect the investment decisions in the forest products industry. The next section reviews previous investment location studies. This is followed by a demonstration of the CLM and TSCS model and by a description of the data set. Finally, the empirical results from the two models are presented, and policy implications are discussed.

LITERATURE REVIEW

Previous studies of industrial growth and investment location have taken many forms. The survey approach has been among the primary streams of research, and previous survey studies concluded that location decision is a two-step process (Schmenner 1978). Firms first decide on a general multi-state region and then choose a state or a city within that region, using different criteria in each step. More recently, empirical analysis using secondary data has gained its popularity in evaluating how state and local policies have influenced growth, branch plant location decisions, and new firm start-up decisions (e.g., Bartik 1988; Levinson 1996). This study adopts this latter approach, and the following review concentrates on the related technical issues and empirical results.

Measurement of Variables and Estimation Methods

Studies of industrial investment location have been focusing on the possible causation between the economic characteristics of a region and its industry growth. On one hand, economic growth and investment in a region can be measured fairly accurately in several ways, and different econometric techniques have been applied to analyze them. Employment has long been assumed to reflect the investment and economic growth in a region (Newman 1983; Duffy 1994). Investment expenditure in a certain time period is also considered to be similar to the employment rate. In both cases, a linear regression method can be used. More recently, with the progress made in econometrics, the number of firms that have invested in a region has been linked to the region's attributes using a conditional logit model (e.g., Bartik 1985, 1988; Levinson 1996). The latter approach presents a different way to look into business location decisions.

On the other hand, many economic characteristics for a region (independent variables) are difficult to measure and have been inadequately measured. For example, many previous studies have used the tax effort and capacity indexes from the Advisory Commission on Intergovernmental Relations (ACIR). Lately, even this simple tax average at state level is no longer available since the ACIR was terminated several years ago. No federal statistical agency collects comparable data across states and local areas on business tax rates. Some research groups do publish data on business tax rates, but in many cases they fail to control for differences across states and local areas in how the tax base is defined. Some studies used cross-sectional data and regression to avoid the lack of the continuous time series data (e.g., Duffy 1994).

Aggregate vs. Micro Data

Statistical agencies often collect data from establishments and then aggregate them for publication based on industrial sectors and geographical regions. Many growth and investment studies have used this kind of aggregate data on employment, capital, or value added in a region (e.g., Newman 1983; Plaut and Pluta 1983; Helms 1985). However, the aggregate measures of regional economic activities reflect a number of different types of decisions: small business start-up, new plant, expansion or contraction of production at existing plants, and plant closure. These different types of decisions are presumably made in different ways. For example, high unionization of the labor force may deter possible new investment in a region. But high unionization may also delay the closing of an existing firm and even may succeed in forcing the firm to enlarge its capacity. Thus, the ultimate effect of unionization on economic growth is uncertain (Crandall 1993). This issue makes the specification of estimation equation difficult and may partly explain why many previous studies could not find significant effects for many attributes.

Problems with modeling aggregate business growth patterns make studies on particular types of business location decisions, such as new branch plant, more attractive. For a specific type of business location decision, the appropriate specification of an estimation equation may be more apparent to the researcher. Thus, a focus on a specific type of location decision using micro data makes coming up with a theory-based empirical specification easier (Bartik 1991).

Unfortunately, in many cases, using micro establishment data is prohibitively expensive if not impossible. In fact, the relatively heavy use of aggregate data by researchers and policy analysts is more a reflection of supply rather than demand (McGuckin 1993). In light of data constraints, previous studies on industry growth suggest that a state is still the best unit of analysis when regional influences are being studied. With the state level data, variation in business investment has been explained by state attributes such as tax rate, wage rate, population density, and energy cost (Duffy 1994; Wheat 1986).

Change vs. Level

A longstanding controversy in business location research is whether growth in business activity in a region should be seen as a function of levels of relevant state attributes or changes in state attributes, or both levels and changes (Sullivan and Newman 1988; Bartik 1985). A disequilibrium view of regional economic structure assumes that profit level differences exist among regions and that business growth responds to these profit level differences. Therefore, industry locations are indirectly related to the differences in the levels of state attributes that affect profits. A simplistic equilibrium view assumes that profits are initially equal across regions and that only changes in a region's characteristics can cause changes in its economic activity. A more sophisticated equilibrium view would allow for the possibility that national or international economic forces may lead to expansions in certain industries and that this expansion need not be distributed equally across all regions.

Duffy (1994) criticizes that some studies have used change variables where level variables are called for. However, deciding on, *a priori*, whether to focus on changes or levels or both in modeling aggregate regional economic activity is difficult. Bartik (1985, 1988) argues that a focus on one specific type of plant location decisions would allow for a much cleaner and more plausible model. In both of his studies, Bartik (1985, 1988) focuses on new plant births and uses level variables.

Empirical Results

Only a few of many previous investment location studies have briefly touched the forest products industry in cross-industry comparisons. Duffy (1994) analyzes 1954-1987 state manufacturing employment growth in 19 two-digit industries over 50 states in the U.S. The market variables are found to have the strongest influence in 18 industries, followed by labor variables. As to the wood products industry (SIC 24), market, transportation, and income variables had significant influence on employment growth. For the paper industry (SIC 26), the unionization variable had a negative coefficient, while the effect of market was positive. However, no effect is found for government policy and resource endowment factor, which is represented by, perhaps erroneously, commercial forest holdings. Levinson (1996) uses establishment-level data to examine the effect of differences in the stringency of state environmental regulations on establishment location choice. Using the conditional logit model, he shows that interstate differences in environmental regulations do not affect the choice of location by most manufacturing plants. For the forest products industry (SIC 24 and 26), the model was estimated for new branch plants of large firms. No environmental variable has been found to be significant.

METHODOLOGY

The conditional logit model (CLM) and the TSCS model are used in this study to evaluate the investment activities of the forest products industry in the southern U.S. This is in accord with the two popular ways of measuring investment activities—the number of new plants and total investment expenditure. The development and estimation of the CLM is more complicated than the TSCS model, and most of the following description is devoted to the CLM.

Conditional Logit Model for New Plant Births

First developed by McFadden (1974), the CLM has been used in various economic analyses, especially the interregional studies of plant location. Following Carlton (1983), each new plant is assumed to have a latent (unobserved) profit function that is dependent on the attributes of the state in which it locates or it is intended to be located. Firms evaluate all relevant state attributes and seek locations with the highest expected profits. Firm i selects state j if and only if the profit derived from the choice, π_{ij}, is at least as great as π_{ik} for all k, which are in the set of alternative choices (states) available to firm i. Thus, the profit π_{ij} that each individual firm derives from locating in a state can be written as a function of the attributes of that state and a disturbance term:

(1) $$\pi_{ij} = \beta' X_j + e_{ij}$$

where X_j is a vector of observable attributes for state j, β is a vector of coefficients, e_{ij} is a random disturbance term, 'i' indexes firms, and 'j' indexes states.

The probability of selecting a specific state depends on the attributes of the state relative to those of all other states in the choice set. If the e_{ij} is independently and identically distributed and has a Weibull density function (McFadden 1974), then the probability of a new firm i choosing state j will be given by

$$\Pr ob_j (Y_i = j) = \frac{e^{\beta' X_{ij}}}{\sum_{k=1}^{m} e^{\beta' X_{ik}}} \tag{2}$$

where Y_i is the index of the choices made by firms, 'm' is the total number of states, and both 'j' and 'k' index the states.

Estimates of coefficients β can be obtained by maximizing the following likelihood function.

$$L(\beta) = \prod_{j=1}^{m} \Pr ob_j \tag{3}$$

The rather strong assumption in CLM is that the disturbance terms are independent across the alternatives. This is so-called "independence of irrelevant alternatives (IIA)," meaning that the relative probability of choosing one of the two existing alternatives is unaffected by the presence of additional alternatives (Greene 1996). If the alternatives are very similar, this assumption may be too restrictive.

Hausman and McFadden (1984) propose a specification test for this model to test the inherent assumption of IIA. The procedure is to estimate the model with all choices and the alternative specification with a smaller set of choices. Then a statistic is constructed according to the estimators and covariance matrices. If the IIA test fails, a sequential logit model can be used instead.

The estimated coefficients in the above model could be transformed to the marginal effects by differentiating Equation (2) with regard to the vector of state attributes X. Furthermore, two types of elasiticities can be obtained from the marginal effects. One is the direct elasticity ε_{jn}, showing the percentage change in the probability that state j is chosen in response to a percentage change in the n^{th} explanatory variable for state j. It has the same sign as the estimated coefficients. The other is the indirect elasticity ε_{kn}, caused by the substitution effect that a change in one attribute of a state would cause a change in the likelihood of firms choosing other states. It shows the percentage change in the probability that state j is chosen given a percentage change in the n^{th} explanatory variable for alternative state k (where $j \neq k$). The indirect elasticity has the opposite sign comparing to the direct elasticities and estimated coefficients. Generally, both elasticities are calculated at the mean of the state attributes X_{jn} or X_{kn}. The direct and indirect elasticities can be calculated as the following (Greene 1996):

(4) $$\varepsilon_{jn} = \frac{\partial \ln P_j}{\partial \ln X_{jn}} = \beta_n X_{jn}(1 - P_j)$$

(5) $$\varepsilon_{kn} = \frac{\partial \ln P_j}{\partial \ln X_{kn}} = -\beta_n X_{kn} P_k$$

TSCS Model for Investment Expenditure

When the investment activities in each year for each state are measured by investment expenditure, the data have a cross sectional aspect and a time series aspect. The TSCS model can estimate this kind of panel data as follows:

(6) $$Z_{st} = \gamma' X_{st} + \mu_{st} \qquad s=1...N,\ t=1...T$$

where Z is the investment expenditure, X is the vector of state attributes, γ is the coefficient vector, 's' indexes the states, and ‘t' indexes years. The coefficient vector is assumed to be constant over time and for all groups. There may exist groupwise heteroscedasticity, cross group correlation, or within group autocorrelation for the error terms. All of these can be statistically tested using the likelihood ratio (LR) test (Greene 1996).

MODEL SPECIFICATION AND DATA

In constructing the CLM, one must first specify a set of alternatives that would have been considered by individual firms. The southern states form a well-defined choice set for the forest products industry as they have similar climate, culture, and forest resources (southern pine and hardwood). In this study, nine southern states are selected. They are Alabama, Arkansas, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, and Virginia. Four southern states are excluded from the study, either due to data constraints (Florida, Tennessee, and Kentucky) or because the activities of the forest products industry are not intensive (Oklahoma). In addition, the forest products industry in this study refers to lumber and wood products (SIC 24) and paper and allied products (SIC 26) sectors. The furniture and fixtures (SIC 25) sector is excluded considering that it includes metal and plastic furniture, that wood is just one of their raw materials in that sector, and that firms' investment decisions in SIC 25 sector may be quite different from that in SIC 24 and 26 sectors.

The dependent variable in the CLM is the number of new plants that had been established in the nine southern states from 1991 to 1996. Following the previous location studies, we concentrate on the new plants that allow for better model specification and interpretation of the results. The number of the new plants is obtained directly from relevant state government agencies.[1] For each observation, 1 is assigned to the chosen state and 0 for the other eight states. For the TSCS model, the dependent variable is the "New Capital Expenditure" from the Census of Manufactures and Annual Survey of Manufactures. Due to budget cutback for the survey, no data are available from "Statistics for Industry Groups and Industries" for the period from 1979 to 1981. Therefore, this study will be roughly for the past two decades excluding those three years. For each state, there are 20 observations from 1974 to 1978, and then from 1982 to 1996.

The vector of explanatory variables includes nine state attributes. Individual attributes are selected based on their relevance to the underlying profit maximization hypothesis, and they cover both demand-side variables as well as supply–side variables. The following explains the attributes in detail. A summary of the variables, including data sources and expected signs, is presented in Table 1.

Market

The southern U.S. has been one of the fastest growing regions in terms of population in the last half century, and considerable growth of economic activity has been observed in this area. One of the

[1] The new forest product plant establishments from 1991 to 1996 are obtained from the corresponding Department of Commerce for North Carolina and Texas; Department of Economic Development for Mississippi, Virginia, Louisiana, and Arkansas; Department of Industry, Trade & Tourism for Georgia; Forestry Commission for Alabama and South Carolina.

incentives for this growth may be that the industries try to move closer to the established and emerging markets. In this analysis, two variables are selected to capture this possible effect. They are the state per capita income (INC) and the state population density per square mile of state land area (POP). INC is expected to have a positive effect on the investment decision. However, the effect of POP is undetermined in previous studies (Bartik 1985).

Resource Endowment

In order to minimize production cost, firms often try to locate plants close to resources. This is especially relevant for the forest products industry because of the bulky nature of wood and the resulted high cost of transporting wood. A variable, INVT, which represents the total forest (both softwood and hardwood) inventory available to forest products firms, is included. The Forest Inventory and Analysis Group (FIA) reports INVT periodically (Harris 1997; Forest Service 1999). For example, for North Carolina, FIA reported inventories, growth, and removals in 1976, 1984, 1990 and 1997. In order to fill in the intervening years for the standing inventory in a state, the following formula is used:

$$I_t = I_{t-1} + G^* - S \tag{7}$$

where G* is the average net growth and S is the timber productions between time t and t-1. Generally, annual growth of forest inventory is relatively stable, and G* is assumed to be constant between two survey years. With the variation of removal rate, the net increment to inventory in any single year may be positive or negative. In some years, data on timber production is not available, and consequently S is assumed to be an average of timber production in years that data is available. INVT is expected to have a positive effect on location decisions.

Southern pine is the primary commercial species in this area and the delivered price of southern pine pulpwood (PULP) is selected to reflect the conditions in the timber market. In addition, since electricity is the primary energy source for both sawmills and paper mills, the average cost of electric energy for industrial users (ELEC) is included. Both PULP and ELEC are expected to have negative signs.

Tax

Economic theory suggests that, at least in short-run, high taxes may deter investment and growth. Corporate income taxes, property taxes, and other corporate and individual taxes add to the cost to firms and may thereby discourage firms from locating in high-tax states. However, time series data for various taxes in a state are not readily available, and this study uses the total annual tax revenue for a state to represent the tax level. Considering the difference in tax base in various states, the tax revenue is divided by gross state product, and the resulted ration (TAX) measures the relative tax incidence in each state.[2] TAX is expected to have negative sign.

Environmental Regulatory Stringency

The question of whether firms' location choices are responsive to the stringency of environmental regulations in a state has been a controversial issue. The conventional intuition is that profit-maximizing firms, when seeking location for new plant and investment opportunity, will tend to avoid investing in states with stringent environmental regulations as regulations will cause them to increase production and transaction costs. However, previous empirical studies have found weak or insignificant effects of environmental regulations (Bartik 1988; Levinson 1996). One possible reason may be the low quality of the existing data on the environmental stringency. This study uses a new, industry-adjusted index of state environmental regulatory stringency (ENVR), which has been created by Levinson (1999). The index is based on estimates of environmental compliance costs for all industrial sectors in each state, and therefore, it controls for states' industrial compositions. Not surprisingly, this cost index is negatively correlated with subjective indices compiled by various environmental organizations. ENVR is expected to have a negative effect on the location decisions.

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[2] Government financial and non-financial incentive programs such as tax abatements, direct state loans, and industrial revenue bonds, and information service are relevant to this study as well. Unfortunately, data on various public incentive programs that have been used to recruit the industry are not available.

Labor

Two characteristics of the labor force that are most widely used in location studies are wage rate and education attainment. Average wage rate per man-hour for production workers in a state (WAGE) is used in this study. The education attainment is represented by the percentage of persons 25 years old and over who have completed high school or more (HIGH). WAGE is expected to have a negative sign while HIGH is expected to be positive.

EMPIRICAL RESULTS FROM THE CLM

Model Estimation and Fitness

The CLM is estimated using the data from 1991 to 1995 first. Table 2 presents the results for the full model with nine state attributes, and the reduced model with eight. For the full model, six out of the nine coefficients are significant at the 10% level and five of these six variables have the expected signs. Personal income and forest inventories have positive effects while population density, electricity cost, and tax have negative effects on investment location choices. The coefficient of pulpwood price has a negative sign but is not significant. Environmental regulation stringency does not show significant negative effect, either. For the two variables related to labor force, the wage rate shows an insignificant positive effect, but the education attainment does show a significant negative effect, which is abnormal. The results of a reduced model without HIGH show that except for the personal income becoming insignificant, all other variables show similar significance and magnitude. The reduced model is chosen for the following analysis.

In addition to most coefficients having the correct signs, the model fit the data well. Overall, the regression is significant according to the chi-square test of the log-likelihood ratio, which is similar to an F-test in ordinary regression. The model also passes the Hausman and McFadden test about independence of irrelevant alternatives. An additional, more intuitive, measure of goodness of fit appears in Table 3. It shows the actual and estimated number of new plants in each state along with the percentages. In order to aid in the interpretation of how the model fits the data further, a mean absolute percentage error (MAPE) statistic is created. The MAPE is the average of the absolute difference values between the sample and predicted percentages for each state. In this case, the actual MAPE value implies that the average error of the model in placing an investor's choice of state is only about 2.0 percent.

Elasticity Estimates

From a policy perspective, the estimated elasticities are likely to be more useful because they allow policy makers and industrial executives to identify quantitatively the sensitivity of investment in a particular state to changes in the state attributes. Table 4 presents both the direct and indirect elasticities calculated with Equation (4) and (5). The elasticity estimates show, for example, that if forest inventory (INVT) increases by 10 percent in Alabama, the probability of its being chosen will increase by 19.2 percent, and the probability of other states being chosen will decrease by 3.5 percent.[3]

In terms of mean magnitude of the direct elasticity estimates (1st column of Table 4), tax, with the mean value as high as -2.95, is the most important state attribute that affects new plant location of forest products industry firms. Except for Georgia, tax has the biggest value for all other states. Although there is some variation of the effect of a state attribute in each state, energy price (-2.21), forest inventory (1.97), and population density (-1.45) are the second most important variables for all states and have the same sequence of importance except for Georgia, South Carolina, and Virginia. Consistent with their insignificant coefficients, the state per capita income, timber price, environmental stringency, and wage rate all have low direct elasticities, indicating that these factors have small effects on location decisions. Indirect elasticities show a similar pattern.

Prediction

In order to assess how well the model predicts outcomes, an out-of-sample test is performed using the 1996 data. Using the estimates reported in Table 2 and substituting the state attributes in 1996 into equation 2, the predicted probabilities for investments in 1996 are computed. Table 5 presents the actual and the model's predicted investment number, along with the percentages and MAPE. Alabama actually received 18 new plants compared to the predicted 16 from the model. Similarly, the model under-predicts

[3] This is an average of the impacts across all other states.

the number of new plants in MS, NC, and SC. On the other hand, the model exactly predicts for TX, but over-predicts for AR, GA, LA, and VA. The MAPE is 3.4 percent and reveals that the model predicts new plant births well.

EMPIRICAL RESULTS FROM THE TSCS MODEL

The TSCS model is estimated with the 20-year investment expenditure for the nine southern states using the maximum likelihood method. According to the LR test, the model adjusted to incorporate groupwise heteroscedasticity and group specific autocorrelation is the best.[4] Table 6 presents the results for the full model with nine state attributes and for the reduced model with eight. With the full model, personal income, population density, forest inventory, pulpwood price, and environmental stringency have expected signs and are significant at the 10 percent level. Electricity, tax, and education attainment do not show significant effects. However, contrary to conventional wisdom, wage rate shows a positive sign and is significant at the 10 percent level in the full model. This may be partly because the variation in wage rate among state is not large. In the reduced model that excludes the wage rate variable, the forest inventory becomes insignificant while other variables have similar magnitude.

To understand the magnitude of the effects, the elasticities are calculated by using the coefficient estimates and the average value of the investment expenditure and state attributes (Table 6). The personal income shows a high elasticity of 0.90. The elasticity is about -0.4 for population density, -0.5 for pulpwood price, and -0.2 for environmental stringency.

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[4] The estimator produces nine sets of results with the combination of various specifications. On the disturbance covariance side, there may be no correlation or heteroscedasticity (S0), groupwise heteroscedasiticity (S1), and cross group correlation and groupwise heteroscedasiticity (S2). On the autocorrelation side, there may be no correlation (R0), autocorrelation and same ρ for all groups (R1), and autocorrelation but different ρ across groups (R2). The likelihood statistics from each two models are used to construct the LR test.

SUMMARY AND POLICY IMPLICATIONS

This study is an initial attempt to measure the effect of state attributes on plant location and investment expenditure for the forest products industry in the southern U.S. A conditional logit model is used to estimate the revealed preference of new plant births and TSCS regression has been used to estimate the new capital expenditure in the forest products industry in the southern U.S. Based on the similarity and difference in results generated from the two models (Table 7), some general conclusions can be drawn.

Firstly, both models reach a similar conclusion about the significant effects of three state attributes: two on the market side and one about the resource. Specifically, both the personal income and population density are significant factors in affecting the investment location decisions of the forest products industry. The positive effect from personal income is reasonable and consistent with expectation. The negative impact of the population density is consistent with a few previous studies. Therefore, it is concluded that the market demand side is two-fold: an increase in personal income in a state makes it more attractive, but an increase in population density has the reverse effect. The results from both models show that forest inventory, as the indicator of availability of raw material, plays an important role in attracting industry's investment to a state. This is contrary to the findings in Duffy (1994) that resource availability, measured as commercial forest holdings, has no effect on the growth in the forest products industry. However, the measures of resource availability in these two studies are different.

Secondly, two models produce opposite results for two other resource variables (stumpage price and electricity cost) as well as tax and environmental regulation stringency. This can be attributed to the two different aspects of the models. One is that the CLM covers only six-year investment activities since 1991, while the TSCS model covers the past two decades. These different time periods may represent short run and long run linkage between state attributes and investment activities in the forest products industry, respectively. The other is the difference in measuring the investment activities: number of new plants with the CLM and total new capital expenditure with the TSCS model. In CLM, no consideration is given to the amount of capital investment since data from some states does not include all the plant-specific investment expenditures. On the other hands, the total capital expenditure includes investment in new as well as in existing firms. Therefore, although similar results from the two models are expected, the inherent difference of the two models may well tell us the different sides of the story. In the short run, tax and electricity cost have negatively affected the investment decisions of new plants in a state, while in the long run the stumpage price and environmental stringency have negative effects on the investment expenditure.

Thirdly, neither model has reached a conclusion about the effects of the characteristics of the labor force. The wage rate and education attainment variables show unexpected significant positive and negative effects, respectively. In addition, it is noticed that both variables exhibit sensitivity to the model specifications. We have tried some other state attributes relevant in this study, including land area, unionization percentage of the labor force, the existing manufacturing activity of the forest products industry, and the outstanding per capita debt of state government.[5] The main results are similar to these reported here.

The limitations of this study may be inadequate measurements of independent variables used in this analysis. Proxies or aggregate measurements that may not capture the subtleties involved in individual plant location are used. Future efforts may be directed into improving the quality of data and model specification.

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[5] In addition, wage rate of all workers in forest products industry has been used in both models instead of the wage rate of the production workers. The two series of wage rates have correlation coefficients around 0.98. Another educational attainment, the percentage of the persons who are 25 years old and over and have completed Bachelor's degrees or more, has been tried, and sawtimber delivered price has been used instead of the pulpwood price. Again, no trial changes the main results. Water resource and industrial land prices have been considered, but no appropriate measurement or data have been found.

The policy implication of this study is straightforward. The competitiveness of forest industry in a particular state depends on the strengths of the interconnected elements, such as resource endowment, domestic demand, supporting industries, as well as government policy. State governments can be more successful in recruiting forest industry by reducing tax and energy costs and increasing forest resources. Attracting capital investment is the first step towards resource-based economic development.

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Table 1. Variable Definition and Data Sources

Variable	Variable Construction	Expected Sign	Source
	Dependent Variable		
	Number of new plants for each state		State economic development agencies (see footnote 1)
	New capital expenditure		USDC-BC, CM-GAS, ASM
	Independent Variables		
INC	State per capita income ($)	+	USDC-BC, SA
POP	State population density (persons/sq.mil.)	?	USDC-BC, SA
INVT	Forest inventory (10^6 ft^3)	+	Forest Service (1999)
PULP	Pulpwood delivered price, S. Pine ($/std. Cord)	-	Timber Mart-South
ELEC	Average cost of electric energy, industrial users ($/kWh)	-	USDC-BC, CM-GAS, ASM
TAX	Annual state tax revenue/gross state product	-	USDC-BC, SA
ENVR	Environmental stringency (index)	-	Levinson (1999)
WAGE	Average wage rate per man-hour, production workers, all industry ($/hr)	-	USDC-BC, SA
HIGH	Percentage of persons 25 years old and over who have completed high school education or more	+	USDC-BC, Current Population Reports

ASM: Annual Survey of Manufacturers;
CM: Census of Manufactures;
GAS: Geographic Area Series;
SA: Statistical Abstract of the United States;
USDC-BC: U. S. Department of Commerce, Bureau of the Census.

Table 2. Empirical Results of the Conditional Logit Model

	coefficient	t-ratio	Coefficient	t-ratio
INC	0.00027*	1.82	-0.00006	-0.56
POP	-0.01957*	-5.44	-0.01627*	-4.76
INVT	0.00009*	4.40	0.00010*	4.67
PULP	-0.00919	-0.74	-0.00775	-0.62
ELEC	-66.26900*	-2.56	-57.36280*	-2.24
TAX	-33.81650*	-1.60[a]	-63.62590*	-3.49
ENVR	-0.33943	-0.71	-0.68074	-1.48 [b]
WAGE	0.05520	0.52	-0.04735	-0.47
HIGH	-0.14486*	-2.91	—	—
Log likelihood		-892.91		-897.20
Restricted log likelihood		-927.23		-927.23
Chi-squared		68.64		60.06
No. of observations		422		422

* Significant at 10% level

[a] the P value is 10.9%

[b] the P value is 13.9%

Table 3. Analysis of the Conditional Logit Model Fitness: 1991-1995

	AL	AR	GA	LA	MS	NC	SC	TX	VA	Total
Sample Number	86	33	72	43	30	50	20	62	26	422
Predicted Number	66	45	76	48	36	42	18	54	37	422
Sample Percentage (%)	20.4	7.8	17.1	10.2	7.1	11.8	4.7	14.7	6.2	100.0
Predicted Percentage (%)	15.6	10.7	18.0	11.4	8.5	10.0	4.3	12.8	8.8	100.0

Mean Absolute Percentage Error 2.0%

Table 4. Elasticity Estimates of State Attributes on New Plant Births of the Forest Products Industry

Attributes	Mean	AL	AR	GA	LA	MS	NC	SC	TX	VA
	Direct Elasticity									
INC	-0.88	-0.80	-0.80	-0.88	-0.82	-0.75	-0.93	-0.90	-0.92	-1.10
POP*	-1.45	-1.13	-0.68	-1.59	-1.42	-0.84	-2.10	-1.88	-0.98	-2.43
INVT*	1.97	1.92	1.80	2.49	1.64	1.84	2.94	1.55	1.16	2.39
PULP	-0.39	-0.38	-0.38	-0.41	-0.41	-0.39	-0.35	-0.43	-0.37	-0.37
ELEC*	-2.21	-1.98	-2.31	-2.26	-1.97	-2.28	-2.56	-2.19	-2.10	-2.25
TAX*	-2.95	-2.88	-3.53	-2.47	-2.53	-3.66	-3.25	-3.44	-2.21	-2.61
ENVR	-0.45	-0.45	-0.45	-0.41	-0.53	-0.45	-0.45	-0.49	-0.39	-0.44
WAGE	-0.58	-0.65	-0.72	-0.53	-0.90	-0.92	-0.50	-0.67	-0.91	0.58
	Indirect Elasticity									
INC	0.11	0.15	0.10	0.19	0.11	0.07	0.10	0.04	0.14	0.10
POP*	0.18	0.21	0.08	0.35	0.18	0.08	0.23	0.08	0.14	0.23
INVT*	-0.25	-0.35	-0.22	-0.55	-0.21	-0.17	-0.32	-0.07	-0.17	-0.23
PULP	0.05	0.07	0.05	0.09	0.05	0.04	0.04	0.02	0.05	0.04
ELEC*	0.28	0.37	0.28	0.50	0.25	0.21	0.28	0.10	0.31	0.21
TAX*	0.36	0.53	0.42	0.54	0.33	0.34	0.36	0.15	0.33	0.25
ENVR	0.06	0.08	0.05	0.09	0.07	0.04	0.05	0.02	0.06	0.04
WAGE	0.09	0.12	0.09	0.12	0.12	0.09	0.05	0.03	0.14	0.06

* Indicates that the related coefficient estimates are significant at 10% level as shown in Table 2.

Table 5. Out-of-Sample Predictions: 1996

	AL	AR	GA	LA	MS	NC	SC	TX	VA	Total
Sample Number	18	6	14	7	12	12	4	11	4	88
Predicted Number	16	12	15	10	5	8	3	11	7	88
Sample Percentage (%)	20.5	6.8	15.9	8.0	13.6	13.6	4.5	12.5	4.5	100.00
Predicted Percentage (%)	18.2	13.6	17.0	11.4	5.7	9.1	3.4	12.5	8.0	100.00
	Mean Absolute Percentage Error 3.4%									

Table 6. Empirical Results of the TSCS regression

	Coefficient	t-ratio	Elasticity	Coefficient	t-ratio	Elasticity
INC	0.027*	5.04	0.90*	0.026*	4.61	0.86*
POP	-2.283*	-3.82	-0.56*	-1.507*	-2.81	-0.37*
INVT	0.007*	2.15	0.43*	0.003	1.00	0.18
PULP	-5.583*	-4.18	-0.68*	-3.662*	-2.88	-0.45*
ELEC	153.696	0.11	0.02	790.073	0.59	0.08
TAX	28.287	0.02	0.00	846.742	0.48	0.12
ENVR	-94.010*	-2.49	-0.29*	-71.654*	-1.90	-0.22*
WAGE	21.670*	2.51	0.48*	—	—	—
HIGH	-1.874	-0.56	-0.34	2.083	0.67	0.37

* Significant at 10% level; number of observations is 180.

Table 7. Comparison of the Results from the CLM and the TSCS Regression

	CLM		TSCS		Conclusion
	Sign	Rank †	Sign	Rank	
INC	Yes*	5	Yes	1	Yes, positive effect
POP	Yes	4	Yes	3	Yes, negative effect
INVT	Yes	3	Yes*	4	Yes, positive effect
PULP	No	—	Yes	2	Opposite effect
ELEC	Yes	2	No	—	Opposite effect
TAX	Yes	1	No	—	Opposite effect
ENVR	No	—	Yes	5	Opposite effect
WAGE	No	—	NC*	—	Uncertain
HIGH	NC*	—	No	—	Uncertain

† the rank is sorted by the magnitude of the elasticities and does not include the insignificant variables and the WAGE and HIGH;
"Yes" indicates that the variables have the expected and significant effects;
"No" indicates that the variables have no significant effects;
"NC" indicates that the effects of the variables are significant but not consistent with theoretic expectation.
* indicates sensitive to model specification.