

economics

# The Pattern of Softwood Sawmill Closures in the US South: A Survival Analysis Approach

Daisuke Sasatani and Daowei Zhang

In this study, the Cox proportional hazards model was used to examine factors influencing sawmill plant closures in the US South from 1995 to 2013. Factors considered were plant structure, plant capacity, and the geographic agglomeration of sawmills. The results show that larger plants were found to be less likely to be shut down, whereas sawmill plants owned by multiplant firms were more likely to be closed. Furthermore, intensive competition was found to be a positive influence on closure rates of sawmill plants, whereas specific locations or how closely sawmills were located to one another was not significant. The results of this study suggest that the trend toward increasing industrial concentration will continue within the softwood lumber industry in the US South regardless of economic conditions.

**Keywords:** Cox proportional hazards model, industrial concentration, competition and industry dynamics, economies of scale, plant agglomeration

In recent decades, the softwood sawmill industry in the United States and other developed countries has undergone a process of industrial concentration (Spelter 2002). In other words, the number of sawmills has been declining, and larger sawmills have been dominating the softwood industry. For example, from 1995 to 2009, the number of softwood sawmills in the United States and Canada declined from 1,258 to 891, whereas the combined capacity in the two countries increased from 150 to 168 million m<sup>3</sup> (Spelter and McKeever 1999, Spelter et al. 2009). In Sweden, softwood lumber production increased 37%, whereas the number of sawmills decreased 28.5% between 1979 and 1995 (Roos et al. 2001). In Japan, as many small sawmills closed their operations, the number of sawmills declined 53.4% (from 13,990 to 6,519 between 1996 and 2010) (Eastin and Sasatani 2013).

Because softwood lumber is one of the most important forest products in the United States, such a drastic change in the structure of the industry draws the attention of forest landowners and policymakers. Often, softwood sawmill closures bring social and economic hardships to rural regions (Weeks 1990) and limit financially feasible management options for small timberland owners (Bailey et al. 1996, Brodbeck 2005). Yet, despite the wide recognition of the important impacts of sawmill closure and despite the fact that plant closures are well studied in the economic and business literature (e.g., Bernard and Jensen 2007), little is known about the actual patterns of plant closures in the softwood sawmill industry.

The purpose of this article is to identify factors influencing sawmill closures in the US South<sup>1</sup> where nearly 60% of softwood lumber in the country is produced and where the number of softwood sawmills declined from 420 to 298 from 1995 to 2009 (Spelter and Goodnow 2013). Specifically, we seek to better understand how internal factors, such as plant size and structure, and external factors, such as spatial patterns, affect the dynamic patterns of softwood sawmill closures in the US South. The next section will present a literature review, followed by estimation models, data, and results. The final section concludes and provides some discussion.

## Literature Review

Plant/firm survival analysis is a branch of business performance study, and there are many plant/firm performance studies in the forest industry. Some (e.g., Välimäki et al. 2004, Crespell et al. 2006, Crespell and Hansen 2008, Hansen et al. 2013) have relied on cross-sectional survey data to search for factors that make plants or firms succeed. Those studies often include subjective perceptions of survey participants and tend to focus on internal factors of firms/plants (Sasatani 2013). Others (e.g., Sun and Zhang 2001, Aguilar and Vlosky 2006, Aguilar 2009, Hagadone and Grala 2012) have used aggregated-level data and focus mostly on external factors. In this study, we try to overcome those methodological shortfalls and to uncover the role of both internal and external factors by applying Cox proportional hazards regression (Cox 1972), a

Manuscript received March 28, 2014; accepted December 22, 2014; published online January 22, 2015.

**Affiliations:** Daisuke Sasatani ([sasatani@uw.edu](mailto:sasatani@uw.edu)), Auburn University, School of Forestry and Wildlife Sciences, Auburn, AL; current affiliation: Center for International Trade in Forest Products School of Environmental and Forest Sciences, University of Washington, Seattle, WA. Daowei Zhang ([zhangd1@auburn.edu](mailto:zhangd1@auburn.edu)), School of Forestry & Wildlife Sciences, Auburn University.

**Acknowledgments:** We thank Dr. Henry Spelter and Forest Economic Advisors for providing data. We also thank Dr. Todd D. Steury for advice on survival analysis and Dr. Hiroo Iimaki for advice on GIS analysis. Finally, we thank Yvonne Williams for editorial assistance.

semiparametric survival model, to longitudinal sawmill closure data in the study region.

Plant shutdown is one of the few unambiguous and observable indicators of plant performance (Bernard and Jensen 2007). In addition, because plant survival/closure is a long-term decision and less affected by short-term shocks, it is less volatile than other popular performance indicators, such as production volume and employment (Neffke et al. 2011). A considerable body of literature on plant closures addresses the relationship between the survival rate of plants and their size (Dunne et al. 1989), plant ownership and structure (Bernard and Jensen 2007), spatial pattern, such as plant agglomeration (Wennberg and Lindqvist 2010), and competition (Sorenson and Audia 2000, Stuart and Sorenson 2003). Empirical studies also reveal that the survival patterns of business are different among industries and regions (Mahmood 1992).

### **Plant Size**

Previous studies in various industries show that the likelihood of plant survival/closure is positively related to the size of the plant itself because of economies of scale (Dunne et al. 1989, Audretsch 1991). When a plant increases its output, it usually reduces its long-run average cost of production (Stigler 1958). In the softwood sawmill industry, empirical evidence suggests that increasing returns to scale generally exist (Månnsson 2003). In addition, larger firms may be able to gain bargaining power over nearby forest landowners and to control stumpage prices (Ashton 2006). Thus, the liability of smallness to survive may exist. However, the relationship between plant size and production cost is often nonlinear because economies of scale and diseconomies of scale often create a U-shaped long-run average cost curve. For example, returns to scale of smaller sawmills are found to be larger than those of larger sawmills in Sweden (Månnsson 2003). Consequently, we predict that smaller plants are more likely to close than larger plants, but that plant size has a nonlinear effect.

### **Plant Structure: Single Plant versus Multiplant Firm**

Firms may expand by increasing the capacity of a single plant or by adding new plants. Compared with single plant firms, multiplant firms may enhance their competitiveness by reducing transportation costs (Greenhut 1956), increasing production efficiency and lowering their exposure of location-specific risk through diversification (Manuj and Mentzer 2008), and transferring knowledge among plants (Ingram and Baum 1997). Because profit maximization is pursued at the firm level, a simple size-based rule for the plant closure cannot be applied for plants belonging to a multiplant firm (Whinston 1988). When a multiplant firm decides to reduce its production capacity, it can simply close one or a few sawmill plants and continue to operate (Bernard and Jensen 2007). On the other hand, a single plant sawmill does not have such flexibility. Thus, we hypothesize that sawmill plants belonging to multiplant firms are more likely to close than single sawmill plants.

### **Spatial Pattern: Density and Location**

Many industries exhibit a cluster, which is defined as a geographical agglomeration of plants operating in the same industry (Krugman 1991, Porter 2003). Geographical concentration of firms/plants of the same industry attracts a larger labor pool (Krugman 1991). As a result, labor and other input materials may be available at lower cost and the demand for related by-products increases inside the cluster (Kelly and Hageman 1999). In addition, firms can

outsource certain business activities and focus on their core business activity (Porter 1980). Finally, knowledge spillovers (Paci and Usai 1999) and competition among firms (Porter 1991) benefit the industry as a whole.

The softwood sawmill industry clusters in North America include the US South, the West Coast,<sup>2</sup> and the Northeast.<sup>3</sup> Historically, wood-processing facilities in North America spatially depend on forest resources (Aguilar and Vlosky 2006, Aguilar 2009). When inputs concentrate geographically and cost more to transport than the final products (Greenhut 1956), minimizing the transportation costs for inputs determines the optimal location of manufacturing plants (Weber 1909).

Yet, firms within the same cluster are not necessarily homogeneous. Within the forest products industry cluster in the US South, it has been reported that geographic idiosyncrasies influence the business operation of plants at the state level (e.g., Sun and Zhang 2001) or county level (e.g., Aguilar 2009, Hagadone and Grala 2012). The presumption of these studies is that each sawmill plant benefits from its location. Those explanations are plausible, but structurally similar plants also compete for scarce resources and, thus, lead to an increase in business closure rates (Hannan and Freeman 1977). In other words, plant concentration may have positive as well as negative spillovers (Sorenson and Audia 2000). Softwood sawmill plants compete with each other to secure raw materials. Sawmill plants also compete for market share as well because demand for softwood lumber is inelastic (e.g., Spelter 1985, Li and Zhang 2006).

Consequently, it is important to distinguish three spatial matters: the location of a plant, density with respect to competition, and density with respect to the number of plants (plant agglomeration). If the effect of intensive competition dominates the performance of sawmill plants, density with respect to competition should lower the survival chance of a sawmill plant. If the effect of plant agglomeration dominates the performance of plants through external factors, such as knowledge spillover, density with respect to the number of plants should increase the survival chance of a sawmill plant. We include all three sets of variables in our model to assess which matters are significant. As softwood sawmill plants compete for timber resources and market share, we hypothesize that plants located in a higher density are more likely to close.

### **Methodology: Time-Dependent Cox Proportional Hazards Regression**

Also known as the duration model in economics or event history model in sociology, survival analysis involves modeling the lengths of time to events, such as a plant closure. Survival analysis is a popular methodological tool in the business and economics field but has rarely been applied in the forest products industry (e.g., Sun 2006). Here, we use the Cox proportional hazards regression model (Cox 1972), which is the most widely used method of survival analysis.

The Cox model starts with a hazard function or rate of plant closure at time  $t$ ,<sup>4</sup> which is defined as

$$\lambda(t, x) = \frac{f(t, x)}{S(t, x)} = P(\text{closure at } t, x | \text{survival to } t, x) = \lambda_0(t)e^{\beta x} \quad (1)$$

where  $\lambda(t, x)$  is the hazard function, which is the ratio of plant closures,  $f(t, x)$ , to all surviving plants,  $S(t, x)$ , at time  $t$  given the

vector of individual covariates,  $x$ ;  $\lambda_0(t)$  is an arbitrary and unspecified baseline hazard function that is a function of time  $t$ ;  $e^{\beta x}$  characterizes how the hazard function changes as a function of  $x$ ; and  $\beta$  is the vector of regression parameters to be estimated.

Then, the hazard ratio (HR), the ratio of the hazard function, for two plants with covariate values denoted  $x_1$  and  $x_2$  is

$$\text{HR}(t, x_1, x_2) = \frac{\lambda(t, x_1)}{\lambda(t, x_2)} = \frac{\lambda_0(t)e^{\beta x_1}}{\lambda_0(t)e^{\beta x_2}} = e^{\beta(x_1 - x_2)} \quad (2)$$

where the hazard ratio between two plants depends only on  $e^{\beta(x_1 - x_2)}$ , the function of the difference of individual covariates of two plants. In other words, the effect of a unit increase in a covariate is multiplicative with respect to the hazard ratio, but the baseline hazard can be ignored. When there are  $n$  distinctive independent observations, the partial likelihood of the Cox proportional hazards model is given by

$$\mathcal{L}_P(\beta) = \prod_{i=1}^n \left[ \frac{e^{\beta x_i}}{\sum_{j \in R(t)} e^{\beta x_j}} \right]^{\delta_i} \quad (3)$$

where the summation in the denominator is over all  $j$  different firms at time  $t$ . For censored cases,  $\delta_i$  is defined to be 0 if an observation is right-censored, whereas 1 if uncensored.

So far, all covariates are time-invariant values. However, most covariates, such as production capacity and level of competition, change over time. To include these time-varying covariates, the Cox proportional hazards model in Equations 1 and 3 can be rewritten as

$$\lambda(t, x(t)) = \lambda_0(t)e^{\beta x(t)} \quad (4)$$

and

$$\mathcal{L}_P(\beta) = \prod_{k=1995}^{2013} \prod_{i=1}^n \left[ \frac{e^{\beta x_{ik}(t_k)}}{\sum_{j \in R(t_k)} e^{\beta x_{jk}(t_k)}} \right]^{\delta_{ik}} \quad (5)$$

where the time period,  $t_k$ , is from 1995 to 2013,  $x_{ik}$  is the vector of the time-varying covariate of firm  $i$  at time  $t_k$ ,  $\delta_{ik}$  is defined to be 0 if an observation of firm  $i$  at time  $t_k$  is right-censored, whereas 1 if uncensored, and the summation in the denominator is over all  $j$  different firms at time  $t_k$ . The partial maximum likelihood method is used to estimate the vector of the coefficient parameter,  $\beta$ . The best parsimonious model is selected, relying on the Akaike information criterion (AIC) and the likelihood ratio test (LRT).

The estimated coefficient in the model translates into a relative hazard ratio in a complex and nonlinear manner. Thus, we use a simulation-based approach (King et al. 2000), under which these coefficient estimates are transformed into a counterfactual hazard ratio to help interpret the relative magnitude of each type of effect on the possibility of closure of a hypothetical plant. In this study, 10,000 draws are taken from the multivariate-normal distribution with a mean at the point estimate of coefficients and a variance matrix as the estimated variance-covariance matrix for the coefficients estimated. The 10,000 simulated coefficients are placed into vectors and simulated to predict the counterfactual hazard ratio of the hypothetical softwood sawmill plant. We graphically report the predicted hazard ratios associated with empirically relevant changes in some independent variables by utilizing the “tile” function (Adolph 2012) of R (R Core Team 2013), while other independent variables are set to be constant. This provides a meaningful inter-

pretation of complex nonlinear models for business strategic implication (Zelner 2009).

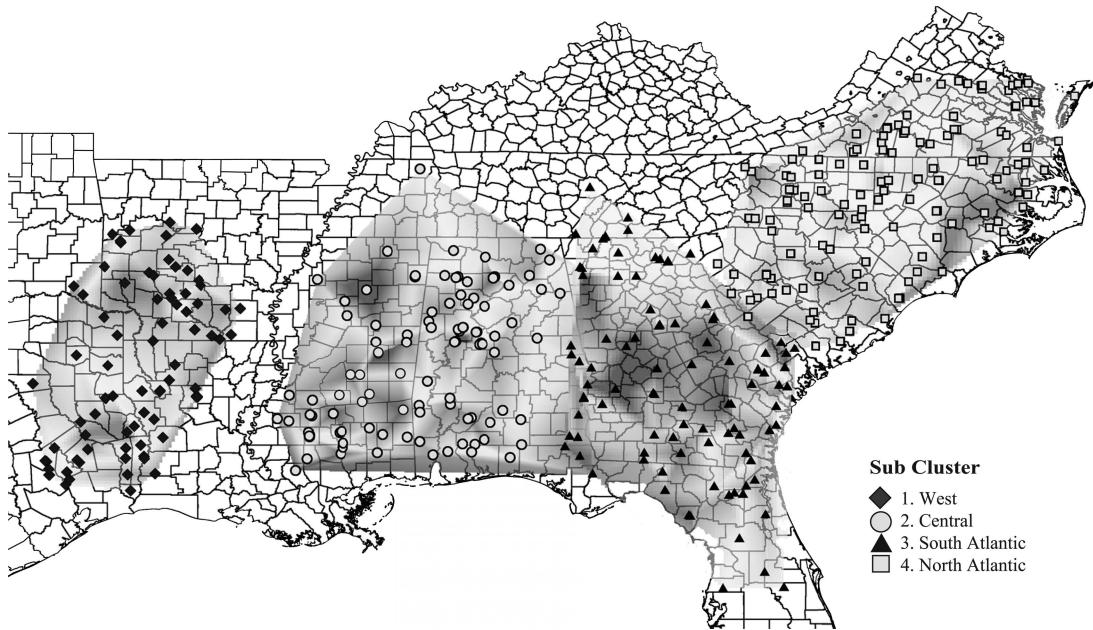
## Data

Our raw plant data are from a series of Spelter’s biennial publications on profiles of softwood sawmills in the United States and Canada (Spelter and McKeever 1999, 2001, Spelter and Alderman 2003, 2005, Spelter et al. 2007, 2009, 2011, Spelter and Goodnow 2013). The data contain plant name, location, the year of closure, the annual production capacity, and the type of lumber produced (i.e., dimension, stud, timber, board, and specialty/unknown). The data cover all 433 major softwood sawmill plants existing in the US South between 1995 and 2013.<sup>5</sup> The unit of analysis of this study is a softwood sawmill plant. We have cross-referenced this information with annual industrial data from *Big Book* by Random Lengths Publications, Inc. (1995–2013). If there is a discrepancy, we have resolved it through contacting sawmill managers, industry organizations, and experts.

Our dependent variable is the time to closure since 1995. Survival regressions usually model time duration since the object of study (i.e., sawmill) became operational. However, the objective of this article is to identify the pattern of industrial restructuring over time rather than a survival duration of each sawmill plant. Therefore, the origin of survival time starts at the beginning of our data or 1995.

Plant closure is the “failed event” of this survival model. We define a plant to have closed at year  $t$  if it produced lumber in year  $t$  but did not produce lumber in year  $t + 1$  with normal business conditions. Ownership changes are not considered as plant closure in this study. In rare cases, some plants might stop operations due to contingent events, such as a fire or upgrading, which was not related to financial distress. If these plants resumed operations within a year, they are not recorded as plant closures. On the other hand, a sawmill plant idled more than a year under normal circumstances is considered a plant closure. Again, because our observation period terminated at the end of 2013, sawmill plants still operating then were recorded as right-censored data.

For our internal independent variables, we have used the annualized production capacity of each sawmill in million board feet (mmbf) as a proxy for the plant size. We cannot use annual production volume as an independent variable because of its endogeneity: the annual production volume is highly volatile and often declines immediately before shutdown. On the other hand, we can assume the exogeneity of annual production capacity. Annual production capacity is a time-varying covariate because firms often invest in increasing the capacity to increase their productivity to gain a competitive advantage. Because firm size generally has a right-skewed distribution (Gibrat 1931), known as Gibrat’s law, a natural logarithm is used to transform the annual production capacity data. Further, the square of log-transformed annual capacity is also included to detect the possible nonlinear relationship between the annual capacity and the time to closure. Second, a dummy variable is used to represent whether a plant belongs to a multiplant firm. The value of 1 was assigned if the firm has at least one other operating softwood sawmill plant in the United States or Canada in year  $t$  and 0 otherwise. Third, to control for the heterogeneity between market segments, five types of sawmill plant are included: (1) specialty/unknown mill, (2) dimension lumber mill, (3) timber mill, (4) stud mill, and (5) board mill. Specialty/unknown mill was set as the base for comparison.



**Figure 1.** Sawmill plant map in the US South. Dots represent the locations of softwood sawmill plants that have operated any time between 1995 and 2013. The four different shapes represent the four different subclusters identified by the hierarchical clustering technique based on geo-coordinates. The spatial interpolation technique is applied to see the spatial concentration of sawmill plants with respect to the annual production capacity. Darker areas have large and spatially concentrated sawmills.

As noted earlier, we have included three sets of external independent variables: plant location, plant density with respect to competition, and plant density with respect to the number of sawmills. We have first obtained the geographical coordinates (i.e., latitude and longitude) of all sawmill plants. By using open-source software QGIS (QGIS Development Team 2014), the straight-line distance between plants is calculated based on the North America Lambert conformal conic.<sup>6</sup> Finally, we have developed three external variables explained in the following paragraphs.

Our plant location is represented by four subcluster dummy variables. We have used a cluster analysis to categorize the subclusters of sawmill plants, based on the distance matrix between each sawmill plant. Because the clustering technique is an unsupervised learning process, the increasing number of clusters and minimization of the target function are always trade-offs. Based on the shape of the dendrogram and knowledge about the industry, we have assigned four different subclusters in the US South based on their geographical coordinates as shown in Figure 1. As a matter of practical convenience, we have named them as (1) West subcluster, (2) Central subcluster, (3) South Atlantic subcluster, and (4) North Atlantic subcluster. The Central subcluster is set as the base for comparison. This set of dummy variables is time invariant.

A weighted localized density, WLD, is used to represent the density with respect to competition for timber resources, for plant  $i$  at time  $t$  (Sorenson and Audia 2000) as

$$WLD_{it} = \sum_j \frac{x_j}{(1 + d_{ij})}$$

where  $j$  indexes all operating plants other than  $i$  in year  $t$ ,  $d_{ij}$  is the distance from the  $i$ th sawmill to the  $j$ th sawmill from the distance matrix, and  $x_j$  is the production capacity of the  $j$ th sawmill plant in year  $t$  as weights. This variable captures the localized density with respect to competition because competitors' locations are weighted

by their capacity size. Localized density is hypothesized as having a U-shaped effect on plants' failure rates (Hannan and Freeman 1977, Carroll and Hannan 1989). Thus, the square of WLD was also included to capture the nonlinearity.

Finally, a nonweighted localized density variable, NWLD, is used to account for density with respect to plant agglomeration (Stuart and Sorenson 2003) as

$$NWLD_{it} = \sum_j \frac{1}{(1 + d_{ij})}$$

This nonweighted indicator considers the localized density with respect to the number of competitors because it accounts for the number of competitors nearby regardless of their size. If positive externalities exist among plants, the coefficient of NWLD should be positive. Both WLD and NWLD are time-variant variables.

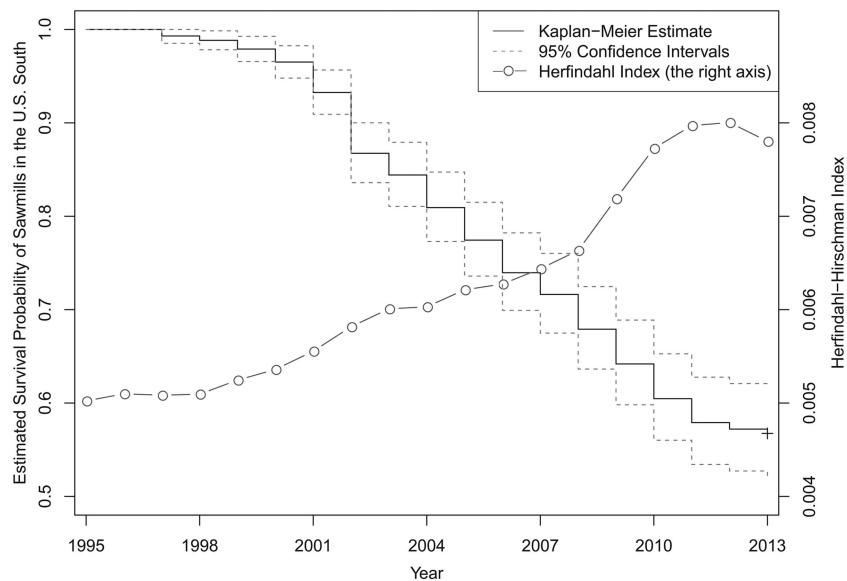
## Results

Table 1 presents the summary descriptive statistics of the independent variables. The mean level of annual production capacity of sawmill plants is 60.2 mmbf and the median is 30 mmbf, which suggests that the distribution of plant size is indeed right-skewed. Figure 2 presents the graph of the nonparametric Kaplan-Meier estimator (Kaplan and Meier 1958) of the survival rate<sup>7</sup> of sawmill plants in the US South based on the raw data. The vertical distance illustrates the probability of plant closure over time. Those distances are roughly constant over the study period. The housing slump in the United States triggered by the subprime mortgage crisis in 2008 severely hammered the southern forest products industry (Hodges et al. 2011). Yet, during the 4-year period of the housing boom, 12.0% of sawmill plants that had existed in 2003 were shut down by 2006. On the other hand, during the 4-year period of the housing crisis era, 15.0% of plants in 2008 were shut down by 2011, which

**Table 1. Descriptive statistics ( $n = 433$ ).**

Continuous variables	Mean	SD	Minimum	Median	Maximum	Proportion	Estimated SD
Production capacity (mmbf/yr)	60.17	65.61	2	30	345		
Weighted localized density (WDL)	83.34	23.34	38.15	81.79	215.3		
Nonweighted localized density (NWDL)	1.559	0.314	0.784	1.559	2.877		
Dummy variables							
Multipiant						0.405	0.491
Type: dimension						0.470	0.499
Type: timber						0.079	0.270
Type: stud						0.049	0.216
Type: board						0.102	0.303
Type: specialty/unknown						0.300	0.458
Subcluster 1 (Central)						0.263	0.440
Subcluster 2 (South Atlantic)						0.228	0.420
Subcluster 3 (West)						0.195	0.396
Subcluster 4 (North Atlantic)						0.314	0.464

The standard deviations of proportions were estimated by  $\sqrt{p(1 - p)}$ .



**Figure 2. Kaplan-Meier estimate and 95% confidence intervals of the survival function for the sawmill plants in the US South and the HHI from 1995 to 2013. Break lines represent 95% confidence intervals.**

is marginally higher but not statistically significant.<sup>8</sup> Thus, sawmill shutdown was not related to the housing boom or crisis. Industrial concentration, the extent to which a small number of large sawmills dominates an industry, is often measured in the Herfindahl-Hirschman index (HHI).<sup>9</sup> As the number of sawmill plants decreased, the HHI gradually increased over time (Figure 2), indicating a trend of industrial concentration.

Table 2 presents the estimation results for the Cox proportional hazards model. The statistical significance of coefficients is based on the Wald test. In the first full model, all internal and external covariates are included. The coefficients of most internal factors are significant, whereas those of most external factors are not. Thus, the next three models cover various combinations of external factors. The LRT is used to compare the fit of two models, as one of them is nested within the other. Our testing hypotheses of the LRT are  $H_0$ : the reduced model is adequate and  $H_a$ : the nested model is better.

In model 1, all four density indexes were excluded. Comparing model 1 and the full model, the full model is better than model 1 at the 10% level as  $\Pr(\chi^2(df=4) > 8.155) = 0.086$ . So, we conclude that a set of spatial density variables helps explain the pattern of plant closure. Then, the two NWLD variables are excluded from the

full model in model 2. Comparing the full model and model 2, the full model is no better because  $\Pr(\chi^2(df=2) > 3.575) = 0.167$ . This means that the two NWLD variables do not affect plant closures, but the two WLD variables do. As noted earlier, WLD reflects the density with respect to competition and NWLD only reflects the density in terms of the number of sawmills. Thus, competition is an important determinant of softwood sawmill plant closures in the US South. In model 3, subcluster dummies are removed. Comparing model 3 and model 2, model 3 is adequate because  $\Pr(\chi^2(df=3) > 6.000) = 0.117$ . This result suggests that plant location does not contribute to plant closure.

Thus, model 3 is the best model in terms of a series of LRTs and Wald tests. In addition, the AIC of model 3 is the smallest among the four models. Therefore, model 3 is set as our final parsimonious model, and we have conducted our simulation analysis based on it. In model 3, the coefficient of the multipiant dummy is positive and statistically significant at the 1% level. The point estimate for the multipiant coefficient is 0.861, which means that the point estimate of the hazard ratio of multipiant is  $HR = e^{0.861} = 2.261$ . This suggests that the closure rate of a sawmill plant belonging to a multipiant firm is 126% larger than that of a single plant firm, all

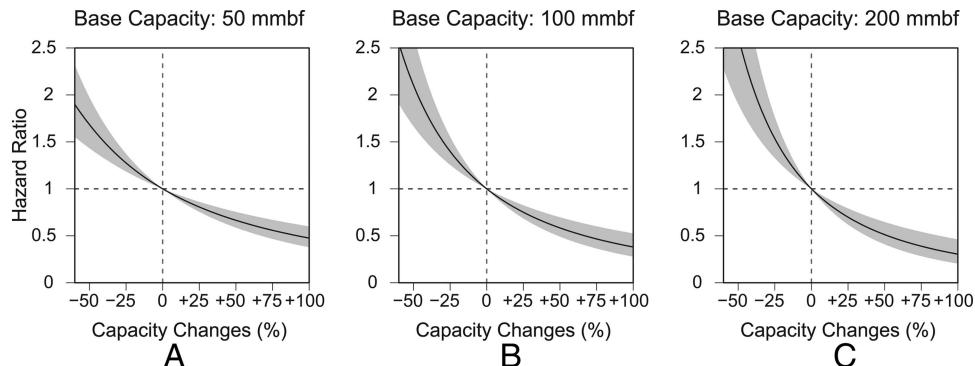
**Table 2. Model estimations of the Cox hazards ratio models.**

	Full model		Model 1		Model 2		Model 3 (best)	
	Coefficient (SE)	$e^{\text{Coeff}}$	Coefficient (SE)	$e^{\text{Coeff}}$	Coefficient (SE)	$e^{\text{Coeff}}$	Coefficient (SE)	$e^{\text{Coeff}}$
<b>Internal factors</b>								
ln(capacity)	0.805 (0.344)*	2.236	0.889 (0.338)†	2.433	0.846 (0.340)‡	2.330	0.889 (0.343)†	2.432
[ln(capacity)] <sup>2</sup>	-0.217 (0.054)†	0.805	-0.226 (0.054)†	0.798	-0.223 (0.054)†	0.800	-0.230 (0.054)†	0.795
Multiplant	0.799 (0.213)†	2.223	0.832 (0.216)†	2.298	0.820 (0.214)†	2.271	0.816 (0.209)†	2.261
Board	-0.615 (0.297)*	0.541	-0.514 (0.291)‡	0.598	-0.542 (0.291)‡	0.582	-0.463 (0.289)	0.629
Dimension	0.330 (0.254)	1.391	0.268 (0.249)	1.307	0.293 (0.253)	1.341	0.262 (0.251)	1.300
Stud	0.827 (0.374)‡	2.287	0.781 (0.371)‡	2.184	0.777 (0.372)‡	2.176	0.767 (0.369)‡	2.153
Timber	-0.053 (0.302)	0.948	-0.136 (0.300)	0.873	-0.076 (0.301)	0.927	-0.127 (0.299)	0.881
<b>External factors</b>								
Subcluster 2	-0.359 (0.236)	0.699	-0.470* (0.224)	0.625	-0.404 (0.233)‡	0.668		
Subcluster 3	-0.066 (0.250)	0.937	-0.133 (0.224)	0.876	-0.066 (0.226)	0.936		
Subcluster 4	0.165 (0.262)	1.179	-0.102 (0.192)	0.903	0.127 (0.247)	1.135		
WLD	0.034 (0.017)‡	1.034			0.031 (0.016)‡	1.032	0.024 (0.013)‡	1.024
WLD <sup>2</sup>	-1.4E-04 (7.1E-05)‡	0.999			-1.3E-04 (6.8E-05)‡	0.999	-1.0E-04 (6.1E-05)‡	0.999
NWLD	-1.551 (1.165)	0.212						
NWLD <sup>2</sup>	0.454 (0.275)‡	1.575						
<i>df</i>	14		10		12		9	
Log likelihood	-1,035.1		-1,039.1		-1,036.9		-1,039.9	
AIC	2,098.1		2,098.3		2,097.7		2,097.7	

\* Significant at the 5% level based on the Wald test.

† Significant at the 1% level based on the Wald test.

‡ Significant at the 10% level based on the Wald test.



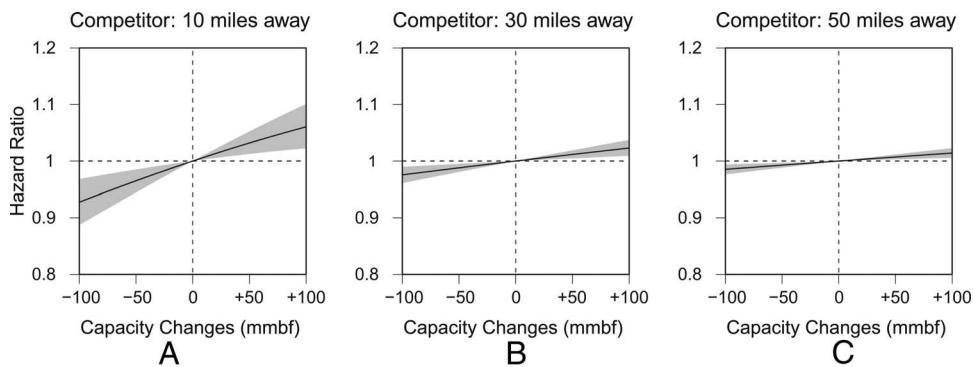
**Figure 3. Hazard ratio for discrete changes in the base capacity of a hypothetical sawmill plant. Gray areas show 95% confidence intervals.**

other things being equal. Further, the closure rate of stud mills is 115% greater than that of specialty/unknown mills. The coefficients for the capacity and squared capacity variables are statistically significant at the 5% level or better. This confirms that plant size influences the closure rate in a nonlinear manner. WLD and squared WLD are also statistically significant at the 10% level or better.

Because the effects of continuous variables are complex and nonlinear, detailed explanations of these effects must rely on simulations. In our first set of simulations, we have three hypothetical plants that have initial annual capacities of 50, 100, and 200 mmbf, respectively. We want to see the variation in their respective hazard ratio as each hypothetical plant proportionally increases or decreases its capacity while other variables are set to be constant. The simulation results are presented in Figure 3. The central lines in the figures represent the point estimates, and the shading represents the 95% confidence intervals around the mean for the respective annual production capacity changes. When each hypothetical sawmill increases its production capacity, its counterfactual hazard ratio decreases and vice versa. However, the decrease in hazard ratio is sharper during the initial capacity increment. For example, if the initial capacity of

a hypothetical 50 mmbf sawmill increases capacity by 10% (5 mmbf), 20% (10 mmbf), and 30% (15 mmbf), its hazard ratio decreases by 8.5, 16.0, and 22.5%, respectively, as shown in Figure 3A. This suggests that a small capacity increment will improve the relative survival rate of a sawmill plant, but at a decreasing rate.

The second simulated scenario focuses on impact caused by a competitor changing its production capacity. In this case, all internal variables of a target hypothetical sawmill are assumed to be constant, and there is a hypothetical competitor whose annual capacity is 100 mmbf that is located 10, 30, and 50 miles away from the target sawmill. As shown in Figure 4, as the competitor increases its annual production capacity, the hazard ratio of the target sawmill increases in all three scenarios. However, the rate of increase in the hazard ratio dissipates as the competitor locates further away. For example, if a competitor is located 10 miles away and increases its capacity by 20, 50, and 100 mmbf, the hazard ratio of the target mill increases by 1.3, 3.2, and 6.1%, respectively, as shown in Figure 4A. On the other hand, if a competitor is located 50 miles away and increases its capacity by the same three amounts, the hazard ratio of the target sawmill increases only by 0.3, 0.7, and 1.4%, respectively,



**Figure 4.** Hazard ratio for discrete changes of a hypothetical sawmill as a hypothetical competitor that is located 10, 30, and 50 miles away changes its production capacity. Gray areas show 1 SD confidence interval.

as shown in Figure 4C. If the competitor that is located 10, 30, and 50 miles away from the target sawmill suddenly shuts down operation (reduced by 100 mmbf), the chance to survive of the target sawmill increases by 7.3, 2.3, and 1.4%, respectively, *ceteris paribus*. The SD of the prediction of impact of WLD is relatively large because physical distance can only partially explain the real competitive situation of sawmill plants. Some omitted variables, such as timberland ownership by sawmills, could complementally explain the level of competition.

## Conclusions and Discussion

In this article, we have investigated the factors influencing softwood sawmill closures in the US South. Larger plants were less likely to have been shut down, whereas involvement in intense competition had a negative impact on sawmill survival. In addition, sawmill plants owned by multiplant firms were more likely to be closed. Furthermore, product type affected sawmill plant survival, but location and the agglomeration of mills did not. This study differs from previous studies in that it examines both the internal and external factors of every sawmill plant in the US South over an extended period of time. This research utilizes the statistically robust Cox proportional hazards model, and the results from this model hold a higher degree of internal validity. This study contributes to the literature in four notable ways.

First, as in many other industries (e.g., Dunne et al. 1989), the likelihood of plant survival in the US South is positively related to the size of the sawmill plant. The existence of economies of scale or the liability of smallness means that sawmill plants will continue to increase their production capacity to sustain their competitiveness, which should further reduce the number of sawmill plants and its coinciding employment within the sawmill industry.

Second, the positive externalities of plant agglomeration or industrial clusters in the softwood sawmill industry might be overshadowed by negative externalities. Positive externalities might have existed when the sawmill industry was being developed, but many factors, such as technology and infrastructure, have changed. To understand this historical path, we applied a four-stage framework of path dependence in economic geography: preformation phase, path-creation phase, path-dependence phase, and path-decay phase (Martin and Simmie 2008). By the 1950s in North America, the ability of sawmill firms to produce lumber had been limited by how fast wood could be supplied to sawmills. Sawmill operations located closer to natural resources had a strong competitive advantage (Cohen and Kozak 2002). This period can be labeled as the “path-cre-

ation” phase. By the 1970s, sawmill operations were limited mainly by technological abilities and how efficiently mills could process available logs, which in turn correlated to the performance of sawmills (Cohen and Kozak 2002). This time period can be labeled as the “path-dependence” phase. Currently, internal competition between sawmills has intensified, and negative externalities exceed the positive externalities of plant agglomeration, so the sawmill industry could be at the beginning or within the “path-decay” phase.

Third, the results of this article can partially explain the puzzling observation of why sawmill closures did not happen at a significantly faster rate during the housing crisis in the late 2000s than during the period of the housing boom as shown in Figure 2. During periods of high lumber demand, sawmill plants often increase their production capacity to make their business competitive, which results in increasing the probability of inefficient nearby plants being shut down. On the other hand, if a sawmill plant closes or reduces its capacity during periods of low lumber demand, the risk of neighboring mills being shut down lowers. That might be the reason why the hazard ratio is fairly constant over time, regardless of a housing boom or crisis.

Fourth, product type affects sawmill plant survival, which suggests that the profitability from different market segments is dissimilar. In this study, board mills shared a higher survival rate during the study period, and stud mills shared a lower survival rate. Stud is typically treated as a price-sensitive commodity, so consumers are more apt to buy the cheapest studs available. On the other hand, some board products are value added and differentiated by consumers, and thus board mills might be able to avoid intensive price competition (Sasatani 2013). However, generalization of these results requires extreme caution because the categorization of sawmills relied on secondary data. Investigating the heterogeneity of consumer markets of various forest products should continue to build on the results of this study.

Note that the variables representing time-specific “shocks,” such as lumber demand and/or any institutional changes, were not included in our model because of the key assumption of “proportional hazards.” In other words, those time-specific shocks are assumed to affect the business conditions of all sawmill plants equally at that time (i.e., sawmill-invariant). Because idiosyncrasies of internal managerial resources of sawmills alone cannot explain the overall pattern of economic performance and survival in the industry (McGahan and Porter 1997), more attention being paid to the role of market structure and competition (e.g., Bain 1951, Porter 1985) on longitudinal performance of the forest products industry is needed

in a future study. Last, survival patterns of sawmills are not necessarily similar in different regions/countries because the business environment and competitive drivers of sawmills are different from region to region. Investigating the survival patterns of different regions can enrich the study field.

## Endnotes

1. The US South includes Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Oklahoma, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia. Although a few sawmills in Maryland utilized southern yellow pine and could belong to the industrial cluster in the US South, we exclude them from this study.
2. West Coast includes coastal and inland regions in the United States and Canada.
3. Northeast includes the northeastern United States and eastern Canada.
4. Time  $t$  is treated as discrete data, and the interval is one calendar year for this study.
5. There were 420 sawmills in 1995, and 13 sawmills newly started operations during the study period. Those sawmills produce a great majority of the softwood lumber commercially available in the market. Portable operations, secondary manufacturers, and very small sawmills were not included in the data.
6. This calculation involves taking spatial coordinates (latitude and longitude) and transforming them to an XY (planar) coordinate system.
7. The survival rate is expressed as cumulative survival rate of sawmills from 1995  

$$S(t) = \frac{\text{number of plants surviving at time } t}{\text{total number of plants in 1995}} = 1 - F(t)$$
8. The null hypothesis is that there is no difference between the two periods. According to a  $Z$ -test, the  $P$  value is  $\Pr(Z > |1.115|) = 0.265$ . Hence, we have failed to reject the null hypothesis at the 10% level.
9. The HHI =  $\sum_{i=1}^{N(t)} s_{it}^2$ , where  $s_{it}$  is the share of total production capacity of sawmill plant  $i$  at time  $t$  in the softwood lumber industry in the US South. Here, the unit of analysis is a sawmill plant, so  $N(t)$  is the total operating softwood sawmill plants in the US South at time  $t$ . If one uses the firm as the unit of analysis, the HHI will inflate because some sawmill plants belong to a few multiplant firms.

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