STATISTICAL ANALYSIS OF SOUTHEASTERN UNITED STATES TIMBER PRICES BY REGIONAL MARKETS, THREE-TIER PRODUCT DIFFERENTIATION, AND LOGGING MARGINS

by

MACIEJ DOMINIK MISZTAL

(Under the Direction of Jacek Siry)

ABSTRACT

Three different aspects of timber markets were addressed using 40 years of quarterly price data provided by Timber Mart-South for 22 regions in 11 southeastern States. Markets for pine sawtimber (PST) and pine pulpwood (PP) were determined across regions using one-price cointegration and accounting for endogenous structural breaks. The PST markets could be interpreted as nine minimarkets or six markets that were driven by three independent markets made up of the largest mill-capacity regions. The PP markets were one major market that spanned from northern Georgia to southern Texas (seven regions) and four markets made up of two regions. Compared to earlier studies, the markets were more fractured. The timing of endogenous breaks was consistent across regions, with breaks in the early 1990s for PST and PP and again in 2007–08 for PST. Causality among prices of PST, PP, and chip-n-saw (CNS) from southeastern markets in the United States was determined using the Granger causality test. Based on the number of significant predictabilities, the strongest causality was for prediction of CNS from PST, and the weakest was for prediction of PP from CNS. Of all the regions, the highest number of significant causalities was in northern Alabama and southern Georgia; no causalities were significant in southern Arkansas and northern Louisiana. Stumpage and delivered pine prices plus their differences were also analyzed with Granger causality tests. For both PST and PP, fewer than 40% of regions had significant delivered-to-stumpage causality, but more than 80% of regions had significant stumpage-to-delivered causality. Accounting for breaks and seasons had an effect for PP but not for PST. Effects of other factors were examined for southern Georgia. Mining/logging wages and midwestern housing starts were significant for stumpage and delivered prices. Industrial production and average hourly construction wage were significant for differences between stumpage and delivered prices. Industrial production was significant for delivered but not stumpage prices. In contrast, the 10-year treasury rate was significant for stumpage but not delivered prices. Delivered prices generally affected stumpage prices more; however, causality was dependent on season and breaks.

INDEX WORDS: Time series, Cointegration, Granger causality, Pine sawtimber, Pine pulpwood, Chip-n-saw, Stumpage

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BA, University of Georgia, 2006

MA, University of Georgia, 2006

A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2018

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August 2018

DEDICATION

I would like to dedicate this dissertation to my wife, Emily, and my parents, Anna and Ignacy. I am so grateful for their unwavering support and encouragement.

ACKNOWLEDGMENTS

So many different individuals were critical to the creation of this dissertation. I would like to thank my committee, Jacek Siry, Michael Bowker, Peter Bettinger, Thomas Harris and Bin Mei, as well as the Harley Langdale, Jr. Center for Forest Business at the University of Georgia. Bob Izlar was a great help to me early on in my Forest Business experience. My colleagues, Yenie Tran, Harrison Hood and the MFR students provided encouragement and perspective. Kate DeDufour and Charlotte Ann Broun Surrat are the definition of efficiency and professionalism. TimberMart-South and their unmatched resources and awesome staff, including Sara Baldwin, Jonathan Smith, Cathy Law, Matt Gaw and Giles Moree, were invaluable. My fantastic editor, Suzanne Hubbard, improved every page of this document.

Jeremy Petranka, Jeremy Cook and John Stuart Rabon were and continue to be friends, colleagues and treasured mentors. My current colleagues at Integrated Statistics and the National Oceanic and Atmospheric Association have been endlessly supportive. I could not ask for a better team to work with. Anderson Cook, Eric Lewis, Pablo Kienzle, and T. Jackson Keenan have provided much needed laughs, texts and game nights, always at exactly the right time.

Two beloved grandparents passed away during my time in graduate school, Janina Turczyńska and Brownlow Crawford. They would both be pleased to know I have finished! My parents-in-law, Carol and Len Crawford, as well as the extended Crawford and Childers families, provided good humor and admirable patience to me.

They say you can’t choose your family, but our adopted Polish family in Athens proves that’s not true. To the Kochuts, Rzuczidlos, Gaertigs and other members of our wonderful

community, bardzo doceniane. My brother Piotr and sister Christine have saved my proverbial tail so many times over the years with their fierce loyalty and constant steadfastness. My parents, Anna and Ignacy Misztal, who have made a lifetime of sacrifices for our family, have been my constant champions throughout this process. They have my deep respect, unending gratitude and sincere affection. Dziekuje bardzo. Finally, my wife, Emily Crawford Misztal, has been my advocate, confidant and partner in-crime for the past twelve years. Emily walks in beauty, like the night, and has the rare combination of both Dian’s wit and the heart of a golden retriever puppy. This work is for her. Also, I apologize to anyone I inevitably left out. As always, my mistakes are my own.

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CHAPTER 1

INTRODUCTION

The Southeast has become the biggest supplier of timber in the United States (Oswalt & Smith, 2014). Compared with other U.S regions, the Southeast tends to be the leader in private foresty (Cristan et al., 2016). Forest tends to be in private hands rather than public. Moreover, the region has undergone considerable change over the last 40 years (Porter et al., 2014). Trucking has surpassed railroads as the dominant means of transport for providing timber for mills. Timber investment management organizations (TIMOs) have taken advantage of tax incentives to buy land, or the land went to real estate investment trusts (REITs). Technology has greatly changed how labor is used to cut trees and which stands can be economically harvested. Silvicultural practices which lead to more consistent and higher quality timber have become more widespread. Individual landowners have access to much more information than in the past. Bioenergy in Europe and increased industrialization in China have opened up new markets, whereas the decline in newspapers has shifted product priorities. Perhaps the biggest changes were Environmental Protection Agency regulations in the early 1990s including the northern spotted owl being designated as an endangered species (Wear & Murray, 2004) and the mountain pine beetle infestation in the 2010s, which shifted the primary source of lumber in the United States from the Northwest to the Southeast.

Data were provided by Timber Mart-South (TMS) to study characteristics of the timber industry in the southeastern United States. The data included nearly 40 years of quarterly prices from 11 States (Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia), starting from the fourth quarter of 1976 through the second quarter of 2016. Data were collected for individual timber sales reported by region. Each State was divided into two regions after a reorganization from three regions in the first quarter of 1991 (Prestemon & Pye, 2000).

An important issue in forest economics is knowledge of timber markets. The law of one price (LOP) (Uri & Boyd, 1990) suggests that local regions should converge into a single market under specific conditions. Timber production across the Southeast varies greatly throughout the region because of climate, ease of transportation, geography, proximity to ports, soil conditions, and many other factors. This suggests that the market might be segmented. Market integration among 22 regions was examined for pine sawtimber (PST) and pine pulpwood (PP) (Chapter 2). Several previous studies used the TMS data to identify unique markets. Yin et al. (2002) examined PST and PP prices using tests for cointegration. They rejected the presence of LOP throughout the entire region but did find evidence of subregions that acted as unified markets. Bingham et al. (2003) considered outside policy factors, such as the reduction of timber harvesting on Federal land in 1998. They found that price shocks are more quickly disseminated across Gulf of Mexico and the Atlantic, which creates one large market, but they also found evidence of two separate interior markets in the northern and western parts of the region. Hood and Dorfman (2015) analyzed the dynamics of the TMS stumpage regions using a time-varying smooth transition autoregressive model. Although the markets were linked at the peak of demand due to the housing boom, they tended to segment as the market worsened.

Structural breaks within the southeastern timber industry represent a bigger shift than standard price shocks. The timber industry is constantly changing in terms of the products it produces and the markets it supplies. For example, newsprint demand declined as bioenergy markets accelerated in Europe (Hoefnagels et al., 2014). Pine pulpwood reached capacity for the Southeast, after 3 decades of steady growth (Harris et al., 2005). A unique characteristic of lumber production is an unusually long planning horizon for raw inputs that may make shocks to the market more persistent. All these shocks can cause mills to relocate and can also cause changes in the demand for specific types of timber products. Markets were examined using LOP cointegration and accounting for two types of endogenous structural breaks (Clemente et al., 1998) (Chapter 2). Changes occurring within one quarter of the year can be represented with additive outliers, but innovative outliers indicate a more gradual change that perseveres over time.

Price relationships among timber products are important when considering timber economics. Relationships among PST, PP, and chip-n-saw (CNS) prices from southeastern markets in the United States were examined (Chapter 3). For hardwood pulpwood, mixed hardwood sawtimber, and oak sawtimber in six southeastern States, Nagubadi et al. (2001) found little market integration across regions and the least integration for pulpwood. Zhou and Buongiorno (2005) considered causality tests among southeastern PST and PP prices in relation to forest product prices for the United States including softwood lumber, paper, and wood pulp. They reported that national lumber prices caused southeastern sawtimber prices. The lack of any causality in the pulpwood markets indicated the southeastern pulp markets were noncompetitive, and the lack of a long-term relationship between pulpwood and pulp products suggested that paper mills behave like monopsonists. Mei et al. (2010) looked at the volatility of southeastern prices in softwood sawtimber, softwood pulpwood, hardwood sawtimber, and hardwood pulpwood and found that softwood sawtimber was the most volatile in absolute terms and that capacity had the most explanatory power over volatility. Parajuli and Chang (2015) analyzed dynamics of PST, PP, and CNS prices in the south-central United States; there both PP and CNS prices were major covariates of sawtimber price. Causality among PST, PP, and CNS was studied using Granger causality and an augmented vector-autoregression model (Chapter 3). Granger causality assumes that *z* causes *x* if *x* can be better predicted with *z* than without it. The causality considers exogenous dummy variables and is determined by a modified Wald test.

Stumpage prices are the prices paid to the landowner to harvest marketable trees on a given piece of land (Nieuwenhuis, 2010). Delivered prices are the prices paid to the logger at the gate of the mill. Variation in stumpage prices in contrast to delivered prices includes specifics about harvesting areas. These include incline on which the trees grow, distance from lumber mills, quality of roads to lumber mills, constancy of product, skidding, hauling, and the opportunity cost of capital, insurance, and any other cost associated with getting the appropriate product to the appropriate mill. Loggers are independent agents that contract with landowners and mills separately. Their major costs are fuel for trucks and machinery, labor, maintenance, and repair as well as the cost of the machinery itself and depreciation. They tend to operate in small groups of fewer than 10 on a job, although the capital involved can differ greatly (Baker et al., 2014). To make a profit, they must correctly price the stumpage and the cost of harvesting and delivering the wood. If they underestimate this cost, they will lose money on the haul. The availability of appropriate timberland and the degree of competition among will help establish a gate price.

Although many agencies report stumpage and delivered prices, few studies have examined factors affecting the difference. Sun and Zhang (2006) analyzed timber harvesting margins in the southern United States between 1977 and 2001. They found that real growth rate of harvesting margins has been negative for PP but positive for PST, hardwood pulpwood, and hardwood sawtimber. Harvesting margins for pulpwood were more stable over time and more integrated spatially than for sawtimber because of changing demand and industry structure. Ning and Sun (2014) looked at timber harvesting margins for timber and lumber markets. Their analyses using earlier prices (stumpage/delivered) led to stronger integration than using later prices (delivered/lumber price). The western United States had less market cointegration than the south. Differences between delivered and stumpage prices were analyzed using the TMS data (Chapter 4). In particular, Granger causality with breaks and seasons either ignored or accounted for was examined. Initial focus was on PST and PP the 11 southeastern States. Then additional factors such as wages, housing starts, and fuel prices were examined for southern Georgia, the largest subregion.

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CHAPTER 2

ACCOUNTING FOR EXOGENOUS SHOCKS IN DETERMINING SOUTHERN TIMBER MARKETS[1]

Abstract

Cohesive markets for pine sawtimber (PST) and pine pulpwood (PP) were identified across regions in the southeastern United States. The data were provided by TimberMart-South and included 40 years of quarterly prices across 22 regions in 11 States. The markets were determined using the law of one-price cointegration while accounting for endogenous structural breaks. The resulting markets for PP resulted in one major market spanning from northern Georgia to southern Texas (seven regions) and four markets made up of two regions. The PST markets could be interpreted as nine minimarkets or six markets that were driven by three independent markets made up of the largest mill-capacity regions. Compared to earlier studies, the markets were more fractured. The timing of the endogenous breaks was consistent across regions.

Introduction

Lumber production in the southeastern United States surpassed the western and northern regions of the United States in 1989 and continues to dominate U.S. production (Howard & Jones, 2016). Timber production across the southeastern United States varies greatly throughout

[1]Misztal M, Siry J, Mei B, & Harris T. To be submitted to *Journal of Forest Economics*.

the region because of climate, ease of transportation, geography, proximity to ports, soil conditions, and many other factors (Porter et al., 2014) This suggests that even for a relatively homogenous product, the market might be segmented. The law of one price (LOP) posits that prices for a commodity in a free market should converge over the long term after taking into account travel costs, transaction costs, and other differing costs between regions (Uri & Boyd, 1990). Moreover, an exogenous price shock, such as a natural disaster, should converge back to a single price over the long term. Measuring the presence of dispersions between subregions can determine local spatial market equilibria. By identifying which regions effectively compete as a single market, buyers and sellers can better forecast which shocks from neighboring regions will most directly affect them. Growers can better determine a fair selling price, and producers are better able to plan the location of mills ensuring a stable supply. Although the LOP has been applied to many commodities and other timber products and markets, the Southeast provides a unique opportunity to compare a large number of subregions that face similar macroeconomic conditions while maintaining unique relationships with each other. The Timber Mart-South (TMS) data contain nearly 40 years of quarterly prices from 11 States in the Southeast that are well suited for identifying such markets. This period of time contains distinct structural breaks in the market that significantly affected market behavior across the region.

Several previous studies used TMS data to identify unique markets. Yin et al. (2002) examined pine sawtimber (PST) and pine pulpwood (PP) prices using appropriately specified pairwise Dickey–Fuller tests for cointegration. Grouped regions were further verified with Johansen tests. They rejected the presence of the LOP throughout the entire region but did find evidence of subregions that acted as unified markets. Although their market definitions were restricted to geographically cohesive groups, they found evidence of cointegration between geographically distant regions. Bingham et al. (2003) considered outside policy factors, such as the reduction of timber harvesting on Federal land in 1998.Their results suggested that price shocks are more quickly disseminated across the coast, thus creating one large market. They found evidence of two separate interior markets in the northern and western parts of the region, although those were not defined explicitly. Zhou and Buongiorno (2006) created a space-time autoregressive moving average model to which they applied impulse shocks. Price shocks were neither statistically nor economically significant past the second-order neighbor and took at most a year to disperse. Rather than defining separate submarkets, each region was treated as the center of its own submarket that overlapped with all the other submarkets. Hood and Dorfman (2015) analyzed the dynamics of the TMS stumpage regions with a time-varying smooth transition autoregressive model. Housing starts were used as an outside indicator variable. They found that all the markets were linked at the peak of demand because of the housing boom. Markets tended to segment more as the market worsened.

The previous studies may not fully account for large exogenous structural changes that affect an entire region but may not affect individual markets simultaneously or to the same degree. Such changes may include the Staggers Rail Act deregulation in 1980, changes in harvest on Federal land, Environmental Protection Agency mandates, pest infestations, changing global demands, and other macroeconomic conditions. Structural changes may accelerate or counteract current trends. Even temporary shocks can cause realignment of the opening and closing of plants that changes the inherent lumpiness of the way price may be transmitted. Simple analyses that overlook such changes may lead to spurious relationships between regions. Using unit root tests that take into account structural breaks allows for a significant increase in the power of the tests and prevents spurious correlation Moreover, two price series differenced on one another form a new price series that may be tested for structural breaks. The presence of a structural break in this case is referred to as a cobreak when the direction of the influence is known (Perron et al. 2006). By using methods that find the break endogenously, more information is revealed about the behavior of the market over time (Glynn et al., 2007). Applying the econometric results to practical knowledge of the timber markets in the region over time allows for a more accurate definition of the submarkets. Determining the timing of the break, even when not statistically significant, reveals information about the dynamics of the time-series data and if previous markets may have been overstated (Yin et al., 2002). Also, the timing of the breaks can indicate when a structural shift occurred and which regions were affected.

The structural breaks within the southeastern timber industry represent much more than price shocks. The timber industry is constantly changing in terms of products produced and markets supplied. For example, newsprint demand has declined as bioenergy markets have accelerated in Europe (Hoefnagels, 2014). The structural shifts examined in this chapter are more than the result of normal business cycles and changes in plant capacity utilization. These shocks can cause mills to relocate and can also cause changes in the demand for specific types of timber products. The unique characteristics of lumber production, including an unusually long planning horizon for raw inputs, may make shocks to the market more persistent.

In this chapter, first the statistical methodology used to test for unit roots, cointegration, and exogenously detected structural breaks are detailed. Next, the dataset and how it was modified are described. Third, the results of the unit root tests are presented, the process and problems with determining markets are explained, and market configurations are provided. Finally, the results are compared with those from previous studies, and further research is suggested.

Methods

Cointegration analysis allows evaluation of whether or not markets follow the LOP and behave as one market. Most prices exhibit nonstationary behavior over time. If their first-differences are stationary, they must be integrated of order 1 [I(1)] (Takayama & Judge, 1964). If a combination of two prices can be expressed as a time series that is stationary [I(0)], the two are said to be cointegrated. This implies that price changes in two spatially separated markets are perfectly transmitted over time, adjusting for exogenous factors such as differences in transaction costs.

The augmented Dickey–Fuller (ADF) test is the standard for determining stationarity (Dickey & Fuller, 1979). Assume the true model can be represented as a random walk with drift $y_t = \alpha \ + y_{t-1} + u_t$, where a is the constant drift term, y_{t-1} represents the previous period, and u_t is an independent and term. By including a time trend and differencing, the standard Dickey–Fuller (DF) model can be tested $\Delta y_t = \alpha + \rho y_{t-1} + \delta_t + u_t$ with ordinary least squares. The null hypothesis suggests $\rho = 0$, indicating the time series is nonstationary and contains at least one unit root. It is possible for either α or δ to be equal to zero, and their significance in the equations needs to be determined in order to be properly specified (Hamilton, 1994). The former implies drift, whereas the latter implies a deterministic trend. ADF improves on the standard model by addressing serial correlation by including lag terms of the differenced time series. In this paper, the ADF with both α or δ, as well as an ADF that includes a trend, will be used only if it is statistically significant for an individual data series. Because the prices never start at zero, the possibility of the intercept being nonsignificant is dismissed.

Results of the test are sensitive to the number of lags which need to be determined on an individual series' basis (Cheung & Lai, 1995). If the lag number is too small, serial correlation will remain and bias the test. If the number is too large, the test will lose power. The Akaike information criterion (AIC; Akaike, 1973) is represented as AIC $= 2k - 2ln\ (L)$, where k is the number of estimated parameters and L is the maximum of the likelihood function. The Schwarz information criterion (BIC; Schwarz, 1978) is represented as BIC = $-2lnL + k\ ln\ (n)$, where n is the number of observations, k is the number of free parameters, and L is the likelihood function. Both reward the goodness-of-fit while penalizing overparametrization, although BIC is stricter and has better asymptotic properties.

An alternative to the ADF is the Phillips–Perron test (Phillips & Perron, 1988) which also aims to account for serial correlation and heteroscedasticity in the standard DF test. Rather than lags, it uses a nonparametric approach and adjusts the estimated variance. Compared to ADF, it has the advantage of not needing to specify the number of lags and being more robust to different forms of heteroscedasticity. However, it is more prone to type I errors which incorrectly reject the null hypothesis. Due to its structure, the Phillips–Perron test does not allow trend without drift.

The most robust method implemented will be the ADF generalized least squares (ADF-GLS) test as formulated and developed by Elliot et al. (1996). It uses generalized least squares in place of ordinary least squares in the standard ADF. The advantage of the test is a significant improvement in power. Otherwise, the test is similar to the ADF but on GLS-detrended data. The test significantly improves on Phillips–Perron and ADF in most cases.

Cointegration was tested with pairwise comparisons between stationary data. The resulting array of significant pairings is used to group regions that are cointegrated with all other regions within a group.[2] Standard differencing method was used for the initial pairings. The

[2] An example is included in Appendix A.

differencing approach requires subtracting one time-series of prices from another. The subsequent series can be tested for unit roots using ADF. Given that $Z_t = p_{1t} - p_{2t}$ is a linear combination of two I(1) processes, if the Z_t is I(0), the two price series can be said to be stationary. Compared to regressing one price on the other and testing the resulting residual for unit root, the differencing method has two advantages. First, it is symmetric and switching the order of the two prices does not affect the results. Second, it avoids the simultaneity problem which suggests that both markets could be influenced by the same exogenous factors such as macroeconomic policies or outside information (Engle & Yoo, 1987).

The Johansen method (JH) (Johansen, 1995) tests for cointegration over multiple variables such as potential subregions as a whole. The standard VAR model can be estimated using a vector error correction model (VECM) of the basic form

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t,$$

where y is a $(K \times 1)$ vector of I/I(1) variables (in this case $K = 2$), Π is the $(K \times K)$ long-run coefficient matrix, Γ are the $(K \times K)$ coefficient matrices for every lagged variable, and $\boldsymbol{\varepsilon}$ is a $(K \times 1)$ vector of normally distributed errors that are serially uncorrelated. This is estimated using maximum likelihood. The rank of Π (r) can be at most K and is equal to the number of characteristic roots or eigenvalues that are significantly different from zero. If $0 < r < K$, then r represents the number of cointegrating vectors. Full rank would imply that the original series are stationary, whereas $r = 0$ implies there are no linear combinations that are I(0). With n I(1) series, full cointegration would imply rank $r = n - 1$.

There are two primary methods of evaluating the JH, the trace test and the maximum eigenvalue test (Johansen, 1995). The likelihood ratio of the trace test can be expressed as

$$\mathrm{LR} = -T \sum_{i=r+1}^{K} ln\left(1 - \hat{\lambda}_i\right),$$

where T is the number of observations and $\hat{\lambda}_i$ is the estimated eigenvalue. The null hypothesis is that there are r or less cointegrating vectors. The test begins at 0 rank and works up until the null fails to be rejected. With only two series, there is either rank 1 or 0. Rank 1 implies cointegration. The maximum eigenvalue test is similar but will be omitted as it suffers from the multiple comparisons problem. Moreover, the trace test is more robust to excess kurtosis and skewness (Sjö, 2008).

With the JH, there are five options of models in order of least to most flexible: no deterministic terms, restricted constant, unrestricted constant, restricted trend, trends for both the cointegrating equation and the difference data. The first and the last of these are highly unlikely, leaving us with the choice of the middle three. Juselius (2006) suggests using the Pantula principle of testing from the most restrictive to the least restrictive. When applicable, this principle was followed beginning with the restricted constant specification.

The Zivot and Andrews (1992) model is used to allow for endogenous structural breaks. The breaks are said to be endogenous, because rather than having a predetermined date chosen by the econometrician directly, the test cycles through every period to pick a potential break point which is most favorable for the null hypothesis. The model can take on three forms. The first allows for a change in intercept (A), the second allows for a change in trend (B), and the third allows for both (C). If the null hypothesis can be expressed as

$$H_0\colon y_t = \alpha + y_{t-1} + u_t.$$

The three models can be represented as H_1:

A $\quad \Delta y_t = \alpha + \delta_t + \theta DU1_t + \rho y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t$

B $\quad \Delta y_t = \alpha + \delta_t + \gamma DT1_t + \rho y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t$

C $\quad \Delta y_t = \alpha + \delta_t + \theta DU1_t + \gamma DT1_t + \rho y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t,$

where $DU1_t$ represents a dummy variable that equals 1 for any $t > TB$, where TB is the breakpoint chosen endogenously. This allows for a shift in the intercept. $DT1_t$ is equal to $t - TB$ for any $t > TB$, representing a shift in trend. Model C allows for both. This model only allows for one structural break. The H_0 of a unit root process without break is rejected if ρ is statistically significant. The break point is tested sequentially and is chosen where the ADF unit root *t*-statistic is at a minimum.

Clemente et al. (1998) allow for two endogenously chosen structural breaks, extending the work of Perron and Vogelsang (1992). They consider two different types of breaks. When the breaks belong to additive outliers (AOs), then the change is quick, implying an immediate change in slope with no persistence. The innovative outliers (IOs) imply a more gradual change that perseveres overtime. This allows a change in intercept and slope. The null hypothesis implies structural changes with unit root.

$$H_0: \quad y_t = y_{t-1} + \gamma_1 DTB_{1t} + \gamma_2 DTB_{2t} + \varepsilon_t$$

$$H_1: \quad y_t = \alpha + y_{t-1} + \theta DU_{1t} + \gamma DTB_{2t} + \varepsilon_t,$$

where DTB_{it} is a pulse variable such that $DTB_{it} = 1$ when $t = TB_i + 1$ for $i = 1, 2$. DU_{it} represents a dummy variable that equals 1 for any $t > TB_i$ for $i = 1, 2$. In the case of the IO, the model to be estimated is

$$y_t = \alpha + \rho y_{t-1} + \theta_1 DU_{1t} + \theta_2 DU_{2t} + \gamma_1 DTB_{1t} + \gamma_2 DTB_{2t} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t.$$

Afterwards, all break combinations for the minimum value of the pseudo *t*-ratio for testing if $\rho = 0$ are checked. For the AO, the deterministic part of the model is removed by estimating

$$y_t = \alpha + \theta_1 DU_{1t} + \theta_2 DU_{2t} + \tilde{y}_t,$$

which allows searching for the minimal *t*-ratio in

$$\tilde{y}_t = \alpha + \rho\tilde{y}_{t-1} + \sum_{i=1}^{p} \omega_1 DTB_{1t-i} + \sum_{i=1}^{p} \omega_2 DTB_{2t-i} + \sum_{i=1}^{p} c_i \Delta\tilde{y}_{t-i} + \varepsilon_t,$$

converging to the unique distribution presented in their paper.

Data

The TMS stumpage price data from 11 States were analyzed. Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia each had data from the start in fourth quarter (4Q) of 1976 through the second quarter (2Q) of 2016. Data are collected on individual timber sales from reporters in each region. The data are then checked, aggregated, and compiled by the staff at the Frank W. Norris Foundation. Each State is divided into two regions following a reorganization from three regions in 1Q 1991 (Prestemon & Pye, 2000). In this paper, each region will be identified by its two-digit State code followed by 1 or 2 denoting region number (Figure 2.1). Focus was on the average PST and PP prices. These are chosen because they are the most consistent in definition and the most complete over time. Stumpage prices are used instead of delivered prices as stumpage prices are more relevant to TMS and their subscribers.

Focus was on nominal level prices. Real price data are also analyzed and resulted in similar findings, which are not reported. Usually, the natural log of prices is used for cointegration tests. The most common purpose is that prices tend to grow exponentially over time. This was not true for either PST or pulpwood as seen in Figures 2.2 and 2.3. Although neither exhibited strictly linear behavior, even nominal prices did not exhibit exponential growth. The logarithm of prices are also used when the data exhibit great variability, which is not the case in these data. Cointegration tests on log prices imply an interest in percentage change in price rather than the price itself. Given that all regions use the same currency and that changes in price are likely to be equal in level across regions rather than proportional, log prices are not necessary. Two pieces of data are imputed for completeness. Both PST for TN1 in Q4 1997 and PP for Arkansas region 2 Q4 1985 have gaps replaced with the average of the 4 quarters immediately beforehand and immediately afterwards. Tennessee region 2 data are dropped completely from PP for having several missing entries in succession. The structural break procedures are sensitive to attempts to impute the missing data. The University of Georgia's Harley Langdale Jr. Center of Forest Business' *Wood Demand Report* provided sawtimber mill capacity data since 1995. Pulpwood mill capacity information since 1980 was supplemented by the *Lockwood Post Directory of Pulp and Paper Mills* as well as the *Pulp and Paper North American Factbook.*

Results

No cointegration analysis can be conducted if the initial data are found to be stationary I(0). Table 2.1 displays the results of 12 different combinations of unit root tests, specifications, and information criteria by column. Each region is tested individually. Only regions that appear to be stationary are shown. The table shows PST and PP testing the nominal price series. Empty columns suggest that all series are found to be nonstationary. Generally, the methods shown are more robust from left to right. The above process was used to determine which of the 22 time series are I(1). If they are of higher or lower order, they are not candidates for cointegration with time series that are I(1). For ADF-GLS, interpolated critical values were used for consistent comparisons (MacKinnon, 1994). The ADF-GLS only allows drift or trend, not both. The number of lagged terms used is determined by either the AIC or BIC. The Phillips–Perron test does not apply lags, but Newey–West estimation (Newey & West, 1987) uses lags to develop proper standard errors.

Generally, the BIC tests the null hypotheses of nonstationarity and is stricter than AIC. Phillips–Perron is stricter than either of the other two tests. This is consistent with its reputation for type I errors, especially in small samples (Glynn et al., 2007). According to the theory and the literature, the most robust specification is the ADF-GLS model with trend. This is the case where nominal prices perform worse for BIC. Each series is confirmed to be stationary when first-differenced, proving that there are no l(2) series.

Price differenced PST and PP without structural breaks allow for a baseline comparison to the rest of the models. Both AIC and BIC are used to determine the appropriate number of lags (time-differences) in each pairwise test. Then the best grouping was determined, where every region in a proposed market is cointegrated with every other region within the market at a 95% significance level. Every proposed market grouping is tested using JH at 95% certainty level and found to be fully cointegrated. Groupings that could not pass the test are reevaluated.[3]

The definition of a unified market suggests that all members of the market are cointegrated with every other member of the market and they are all connected. A large market can be broken up by a single territory that prevents a link. Often a region might be cointegrated with two neighbors that are not cointegrated with each other. In this case, a value judgment must be made. The first priority was to match the region with the neighbor that had the most similar list of other cointegrated regions. This tends to favor large markets and leave more single markets. Using this rule, a region that could only be paired with a neighbor that would otherwise be part of a large market would be left stranded. Further judgments took into account outside

[3]Appendix A contains a sample cointegration array. Appendices C and D contains initial groupings.

data. Factors considered included rail and major trucking connections, the presence of large rivers, which would cause bottlenecking at bridges, location of the nearest port, presence of large mills on the border, and relative volumes in production.

Often markets seem to overlap and a decision must be made as to whether to place a region in one market vs. the other. Many of the region pairs that pass as cointegrated are unlikely to be in a unified market. It may be possible that LA2 will actually be in a market with VA2 given that they both contain ports, despite the fact that regions are very different in climate and environment. This argument would not explain why landlocked AK2 is cointegrated with many regions on the other side of the map and not with any of the local regions. TN1 is connected with 18 other regions in the BIC case. A higher number of cointegrated pairings does not necessarily represent more credible market connections. A high number of clearly unlikely/spurious pairwise connections force more value judgments and might indicate results that are more arbitrary. Methods that lead to a higher ratio of plausible to implausible pairs are considered more credible.

The pairwise arrays are also created with methods that incorporated structural breaks. This includes Zivot–Andrews (ZA) with intercept, trend, and both intercept and trend breaks. Clemente, Montañés, and Reyes (CMR) methods with one and two breaks for both AO and IO. There is no statistical test to prove definitively which method is superior, although the 2-break methods are considered more powerful. A primary difference between ZA and CMR is the null hypothesis. ZA has a simple unit root, whereas CMR tests against a unit root with structural breaks. The latter is supposed to protect from spurious rejections (Glynn et al., 2007).

Figures 2.4 and 2.5 consider the nominal price series for GA 1, GA2, NC 1 and AL 2. AL2 and GA2 are two of the biggest producers in the region and neighbors on the coast. GA1 and NC1 are both mountainous regions. Although GA2 is often found to be cointegrated with

GA1, NC1 tends to be an outlier cointegrated with very few other regions. The PST prices suggest at least one break. It is not clear from the figures whether the break(s) are better suited to intercept/AO or trend/IO**.** Overall, PP seems to exhibit shock(s) in the level of price and PST has more smooth changes. Ideally, one would test for the possibility of more than two breaks. This quickly becomes exponentially more complicated, both technically and theoretically.

The fact that the structural breaks are endogenous allows us to check whether the predicted break coincides with believable exogenous events and whether these events affected part or an entire region. Table 2.2 sums up the frequency of structural dates by year. Data are restricted to CMR as both the null and alternative hypotheses contain breaks. The IO is expected to precede AO when accounting for a structural shift at time *t* since AO is an instant shock, whereas IO is gradual. The change after IO would accelerate to a point that would register as an AO shock. For PST, table 2.2 shows clustering around 1991. When considering two breaks, the breaks are still very bunched with the second break occurring during the start of the housing crisis. The early 1990s was a boom time for Southern timber with Northwest industry moving to the southeastern United States. IO tends to be slightly more dispersed compared to AO. Reported breaks that edge up to the 5% buffer of the end of the time series may indicate no good candidate for an interior break. CMR must return the most-likely break(s).

Table 2.2 presents evidence that two shifts have occurred in the southeastern timber market since 1978. The ZA tests for structural breaks in intercept, trend, or both. The CMR test in either AO or IO specifications both test for breaks endogenously. Over two thirds of PST regions show a break in the early 1990s within 2 years. When the CRM 2 break test was applied, 20 of the sawtimber regions show a break between 2006 and 2008 for IO, whereas 21 show a break in 2007 or 2008 for AO. For PP IO with two breaks, 16 regions showed a break between

1989 and 1992, 13 regions show a break between 1996 and 1999, and seven showed a break between 2006 and 2009. For PP AO with two breaks, 15 show a break between 1990 and 1993, 12 show a break for 1996 through 1999, and 9 show a break between 2006 and 2009. Unlike a single shock to a local region, like a hurricane, these structural breaks affect many regions within a relatively short amount of time. Those regions within one market should trend toward equilibrium together.

The suitability of structural break unit root testing on the difference between two stationary processes is identical to that of testing with any other method. The timing of the structural break(s) indicated a permanent or temporary shock to the relationship between two prices. A frequency table of the timing of the paired States can be found in Appendix B. There is no need to assume that all regions in a single market will experience shocks with each other at the same time, although the frequency table does suggest there is bunching. The greater power that comes from these tests provides more assurance that the prices between two markets are indeed correlated and not spurious.

Figures 2.6 and 2.7 show four States from the previous tables with one region’s price subtracted from the other. Given the evidence of price breaks in the individual States, major breaks in the early 1990s and last 2000s for the markets suggest an IO approach over an AO approach. This graph also supports the theory that markets tend to diverge during expansion and converge during contraction in industry cycles (Hood & Dorfman, 2015). An IO interpretation is also possible in pulpwood, which seems more volatile.

Tables 2.3 and 2.4 provide a comparison of a sample of considered methods. Stationary regions are the number of regions found stationary when the test was applied on the single region. Given the stronger power of the test, more stationarity is expected than for the standard tests.[4] The stationary regions tend to be isolated with fewer reports and lower production. The two-break methods do exhibit at least one major region each as stationary at the 5% level. This could potentially make them inappropriate for pairwise cointegration testing. However, structural break models are to be an extension of traditional unit root tests, not a replacement. The major regions that are stationary differ between the AO methods and the IO methods.

Cointegrated pairs are the number of the unique pairs that are shown to be stationary. The number of markets is determined as described above, generally first prioritizing larger regions, then readjusting to eliminate leftover one-region (single) markets, and finally reevaluating using external real-world consideration such as mill locations, natural barriers and ease of transportation. Alternative interpretations would usually increase the number of markets by splintering them but would not greatly change the number of single regions left over.

A higher number of cointegrated pairings does not necessarily represent more credible market connections. A high number of clearly unlikely/spurious pairwise connections force more value judgments and might indicate more arbitrary results as it increases the possible interpretations. Methods that lead to a higher ratio of plausible to implausible pairs are considered more credible.

The markets for PST and PP in the unit root tests over shorter segments show that simply breaking up the data in smaller time periods is not promising. The data set starts to exhibit much greater small sample issues. Although not apparent here, more series tested stationary as the time periods decreased. The sharp increase in stationarity may be a result of the smaller sample properties (Hosken &Taylor, 2004).

[4]The regions are predominantly I(0) as shown in Table 2.1.

Pulpwood markets are more disjointed than sawtimber. Often a majority of regions can be designated as single region markets. The number of cointegrated pairs is also lower. This is probably due to higher proportional transportation cost over revenue for pulpwood. Another factor is the greater lengths mills are willing to take to keep a saw mill supplied over a pulp mill. The CRM with one break stands out as having a comparable amount of cointegrated pairs to sawtimber.

For PST and PP, the CRM IO 2-break structural model has the least spurious cointegration array while giving complete and viable maps.[5] IO is more theoretically sound over AO given that persistent shifts are anticipated in markets between regions rather than one off shocks. Using the cointegration array from sawtimber, two different alignments can be derived emphasizing the need for consideration of practical concerns. The first arrangement in Figure 2.8 tries to incorporate as many regions into markets as possible. Most groupings are composed of timber markets with relatively large mill capacity combined with a market with lesser capacity. The exceptions are FL1 and FL2, which are small capacity markets, AL1 and AL2, which are large capacity markets, and TN1, which is the only single low-capacity market. The issue with this specification is the Arkansas-Louisiana corridor. There is no major freight transportation infrastructure connecting AR1 with LA1, particularly towards the West where most mills are located.

There is a natural alternative specification in Figure 2.9. Grouping decisions are based on freight transportation patterns. An alternative specification of PST markets contains six PST markets with four single region markets left over. Three of the four single markets have the three

[5] See appendix C for AO groupings and Appendix D for baseline groupings.

largest sawtimber mill capacities in the region suggesting their weight has them respond differently to price shocks than the surrounding markets.

For PP in Figure 2.10, contradictory pairings were resolved based on pulp/paper and bioenergy mill locations. Of the five markets, all but one consists of two regions. The 7-region market stretches from TX2 to GA1. The three of the four singletons have mill capacities that tend to be negatively correlated with the rest of the regions and positively correlated with each other. All three have lost more mill capacity proportionally since 1990 than any other region. The exception is VA2.

Discussion and Conclusions

This paper uses TMS price data PST and PP to determine which regions form a cohesive market. The data are used to determine endogenously the structural break points of each price in each region. A majority of the break points occur during periods that have clear explanations for an outside shock. These shocks were more clustered for PST rather than PP. By taking into account structural breaks, spurious connections are reduced between regions that do not behave as one market but were affected by an exogenous shock to the entire region. In the preceding chapter, PST markets either paired large capacity regions with small capacity regions, or high-capacity regions acted as their own single markets. For PP, the market spanned five States. The three markets that have seen the largest decline in capacity were single markets. The three-time periods around which the endogenous breaks cluster represent a significant restructuring for the industry with persistent effects compared to regular business cycles. The early 1990s structural break stems from the declaration of the northern spotted owl as endangered, resulting in severe restrictions in logging in the northwest United States. The southeastern United States absorbed much of the excess demand as it declined in the Northwest. In the late 1990's the pulpwood market reached a turning point where capacity started falling after consumption peaked in 1994 and exchange rates were unfavorable to exports. The housing crisis, which began in 2006, severely affected the timber industry. Although all the regions were affected, the timing and extent of the reactions differed geographically. For instance, Arkansas, Texas, and Louisiana pulpwood were affected by the recession sooner than the rest of the region.

The endogenously determined breaks display a consistent pattern with the proposed structural breaks affecting regions directly. There is no significant bunching at the beginning or the end of the time frame. PST has between 10% and 20% of its restructuring breaks occurring before 1989. PP, which was exhibiting steady growth at the time, had less than 5% breaks prior to 1989. The dispersion of breaks over time is larger for PP than for PST.

The structural changes between regions are expected to be persistent. Compared to the nonstructural baselines,[6] the groupings are more conservative, reflecting the increased power of the tests. The results are less dependent on individual interpretation than previous methods. Six integrated markets were identified along transportation corridors. The three regions with the largest mill capacities are independent. Pine pulpwood has one large unified market ranging from lower Texas to the mountains of Georgia. Three out of the four one-region markets showed the largest proportional downturn in production since the 1990's. In both cases, these groupings survived the restructuring of the industry over the last 40 years. It may be insightful to contrast the nature of the results with those of Hood and Dorfman (2015). Both acknowledge that the market changes over time. Although their STAR model shows ebb and flow of markets quarter to quarter, this study aims to cut through to fundamental relationships that span over transition

[6] Appendix D

periods. The markets evaluated in this paper represent those that have persevered through significant positive and negative shocks to the market as well as the advancements in technology and evolution of the global market. The groupings imply fundamental underlying characteristics (geography, forest resources, transportation infrastructure, etc.) that dispel price shocks more proficiently.

There are several limitations of this study that could be addressed and expanded upon with more data. Further analysis into the markets could be conducted with more complete and detailed production and production-capacity data. Calculating a supply curve would be possible with data on both quantity and price. It would be viable to see how production shifts between regions within a unified market given short-term exogenous shocks or region-wide structural shifts. Elasticities by region could be determined. Demand information would allow the modeling of the complete market. With detailed information about major mill and plant closings and locations over time, it would be possible to expose patterns along the borders of States and see productions shifted from one border to another, verifying a realignment in markets.

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Table 2.1: Region tests for unit roots on nominal price data for pine sawtimber and pine pulpwood[1]

	No trend				Trend added			
	AIC		BIC		AIC		BIC	
Test	PST	PP	PST	PP	PST	PP	PST	PP
ADF	…	AR2* LA1* TN1** TX1* TX2**	…	AR1** AR2* LA1* TN1* TX1** TX2**	…	AR2* LA1* TN1** TX1* TX2**	…	AR1** AR2* LA1* TN1* TX1** TX2**
Phillips–Perron	…	AR2* GA1* TN1* TX1* TX2*	…	AL1* AL2* AR1* AR2* GA1* TN1* TX1* TX2*	NC1** VA1**	AR1* AR2** LA1* LA2** MS2** NC1** NC2** SC1* TN1** TX1** TX2** VA1** VA2*	NC1** VA1**	AL2* AR1** AR2** LA1* LA2** MS2** NC1** NC2** SC1* TN1** TX1** TX2** VA1** VA2*
ADF–GLS	…	…	…	…	…	…	AR2* NC1** TN1* TN2*	…

[1]Tests are more complex from top to bottom and from left to right: ADF = augmented Dickey–Fuller, ADF-GLS = ADF-generalized least squares, AIC = Akaike information criterion, and BIC = Schwarz information criterion. Region is designated as two-letter State abbreviation and region 1 or 2, and regions shown were found to be stationary: * denotes 5% critical value, and ** denotes 1% critical value. PST = pine sawtimber and PP = pine pulpwood.

Table 2.2: Frequency of suggested breaks for pine sawtimber and pine pulpwood using the Clemente, Montañés, and Reyes method and additive outliers or innovative outliers[1]

	1 break				2 breaks			
	PST		PP		PST		PP	
Year[2]	IO	AO	IO	AO	IO	AO	IO	AO
1986	0	0	0	1	0	0	0	0
1987	0	0	0	0	0	0	0	0
1988	0	0	1	1	0	0	2	0
1989	1	1	3	4	0	0	6	2
1990	1	1	6	2	0	0	5	9
1991	13	0	0	5	2	0	2	1
1992	3	3	3	0	9	2	3	5
1993	2	16	0	0	9	15	0	2
1994	1	0	0	0	1	2	1	0
1995	0	0	0	1	0	2	1	1
1996	1	0	1	1	0	0	2	2
1997	0	0	1	3	2	0	7	3
1998	0	1	0	1	0	1	2	1
1999	0	0	0	0	0	0	2	6
2000	0	0	0	0	0	0	0	0
2001	0	0	0	0	0	0	0	0
2002	0	0	0	0	0	0	0	0
2003	0	0	0	0	0	0	1	2
2004	0	0	0	1	0	0	2	0
2005	0	0	1	0	0	0	0	1
2006	0	0	1	1	6	0	3	1
2007	0	0	0	0	10	7	1	2
2008	0	0	0	0	4	14	1	2
2009	0	0	0	0	0	0	2	3
2010	0	0	0	0	1	1	0	0
2011	0	0	0	0	0	0	0	0
2012	0	0	4	0	0	0	1	1

[1] PST = pine sawtimber, PP = pine pulpwood, AO = additive outlier, and IO = innovative outlier.

[2]No structural breaks were estimated between 1979 and 1986; therefore, those years are not shown.

Table 2.3: Comparison of market identification methods in pine sawtimber

Method[1]	Stationary regions	Cointegrated pairs	Distinct markets (≥2 regions)	1-region markets
Standard differences, BIC, no breaks	0	158	4	0
Standard differences, AIC, no breaks	0	154	7	2
Standard differences, AIC, before 1993	1	140	4	6
Standard differences, AIC, after 1992	1	256	6	6
Zivot–Andrews, break, intercept	5	204	7	2
Zivot–Andrews, break, trend	1	200	7	0
Zivot–Andrews, break, intercept and trend	8	236	5	1
Clemente, Montañés, and Reyes, IO, 1 break	1	158	8	0
Clemente, Montañés, and Reyes, AO, 1 break	4	130	9	2
Clemente, Montañés, and Reyes, IO, 2 breaks	6	80	8	1
Clemente, Montañés, and Reyes, AO, 2 breaks	8	118	5	6

[1]BIC = Schwarz information criterion, AIC = Akaike information criterion, AO = additive outliers, and IO = innovative outliers.

Table 2.4: Comparison of market identification methods in pine pulpwood

Method[1]	Stationary regions	Cointegrated pairs	Distinct markets (≥2 regions)	1-region markets
Standard differences, BIC, no breaks	0	162	4	3
Standard differences, AIC, no breaks	0	78	4	8
Standard differences, AIC, before 1993	1	110	4	8
Standard differences, AIC, after 1992	0	68	4	10
Zivot–Andrews, break, intercept	8	106	5	6
Zivot–Andrews, break, trend	3	122	3	9
Zivot–Andrews, break, intercept and trend	7	170	4	6
Clemente, Montañés, and Reyes, IO, 1 break	0	130	6	4
Clemente, Montañés, and Reyes, AO, 1 break	3	134	5	4
Clemente, Montañés, and Reyes, IO, 2 breaks	1	62	6	5
Clemente, Montañés, and Reyes, AO, 2 breaks	4	86	5	5

[1]BIC = Schwarz information criterion, AIC = Akaike information criterion, AO = additive outliers, and IO = innovative outliers.

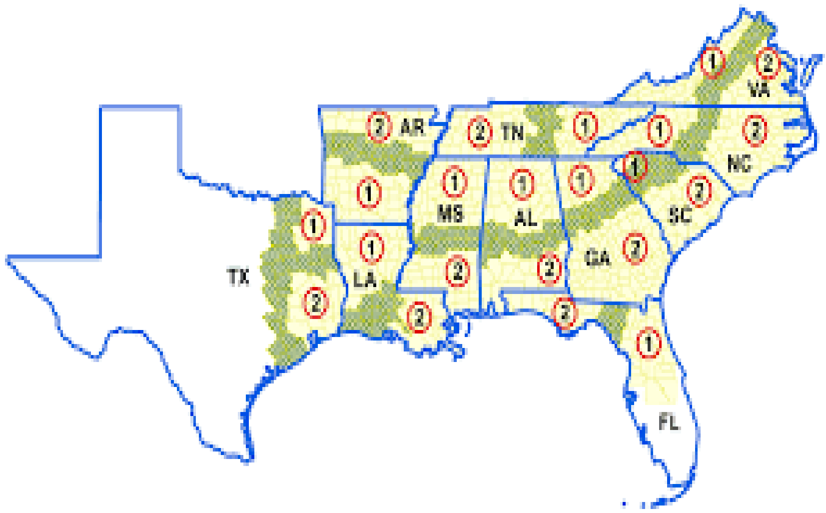

Figure 2.1: Timber Mart-South regions. Region is designated as two-letter State abbreviation and region 1 or 2.

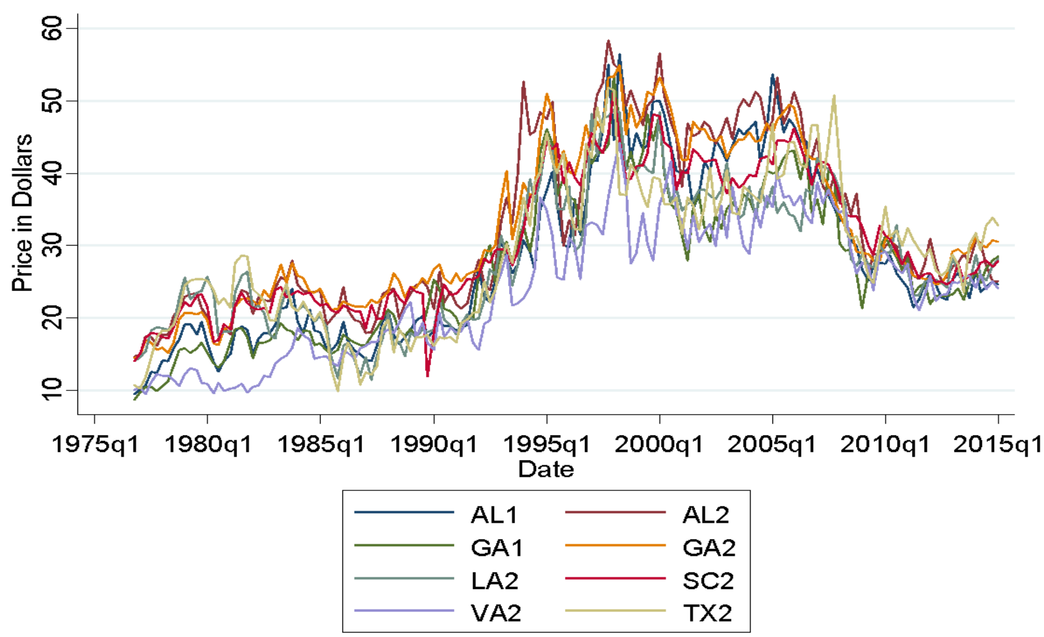

Figure 2.2: Nominal pine sawtimber prices for select markets over time. Region is designated as two-letter State abbreviation and region 1 or 2; q1 = quarter 1.

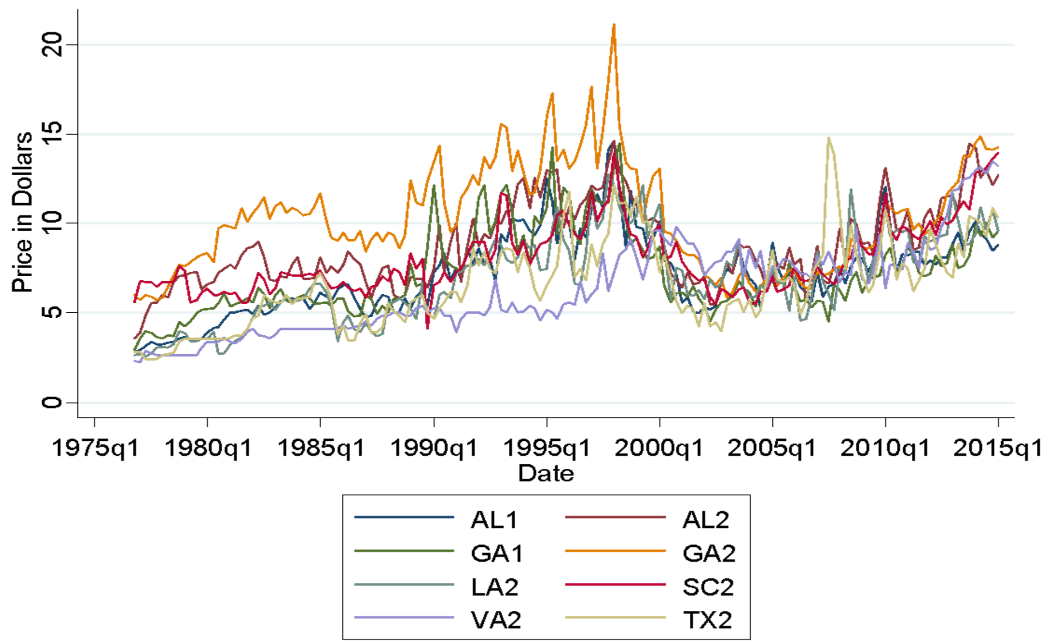

Figure 2.3: Nominal pine pulpwood prices for select markets over time. Region is designated as two-letter State abbreviation and region 1 or 2; q1 = quarter 1.

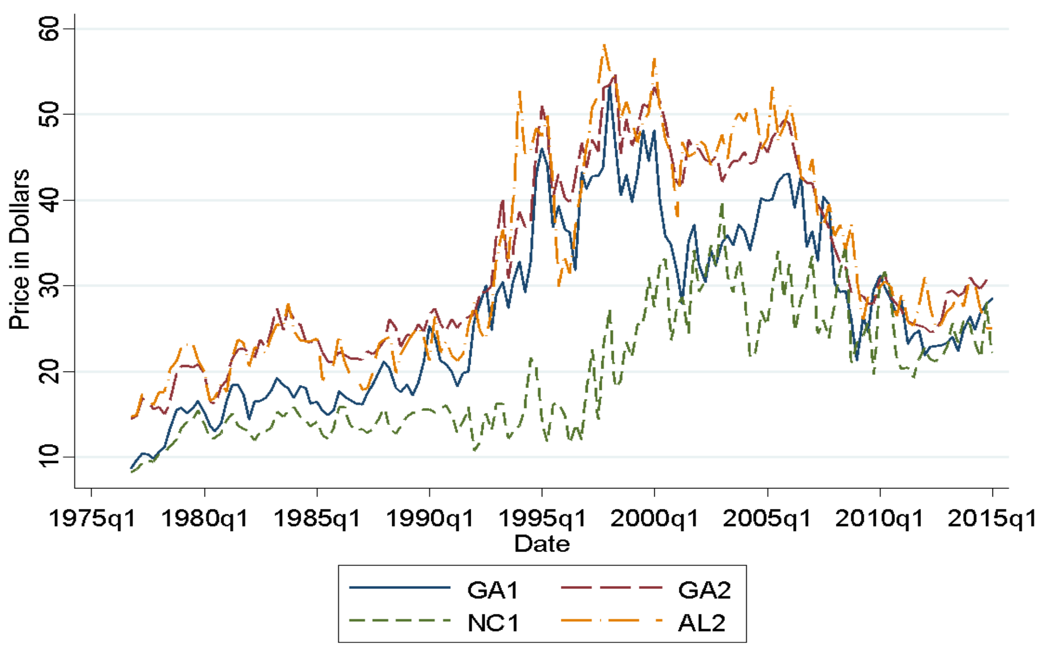

Figure 2.4: Pine sawtimber time-series samples. Region is designated as two-letter State abbreviation and region 1 or 2; q1 = quarter 1.

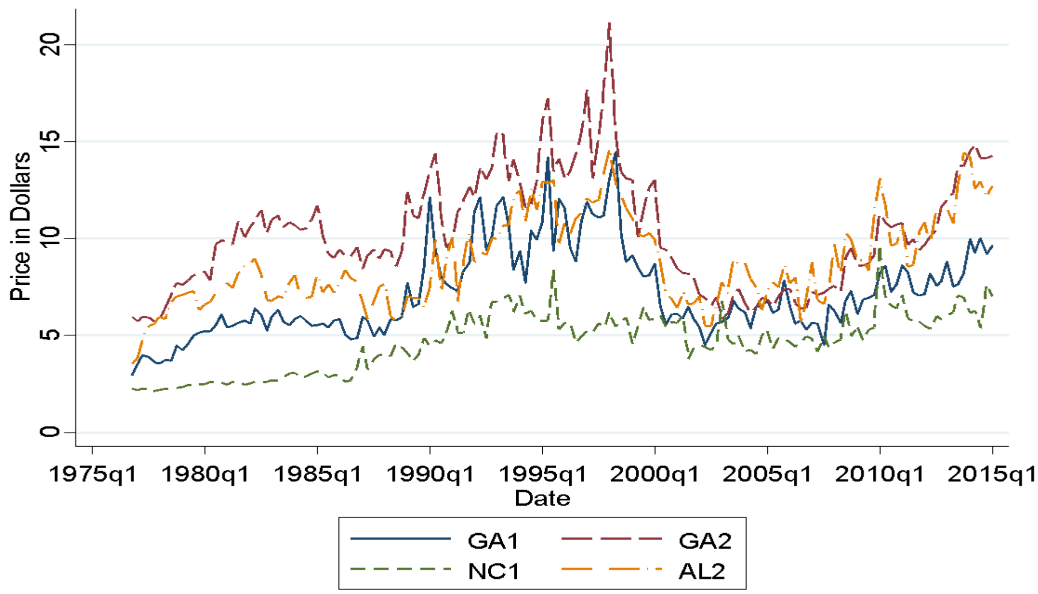

Figure 2.5: Pine pulpwood time-series samples. Region is designated as two-letter State abbreviation and region 1 or 2; q1 = quarter 1.

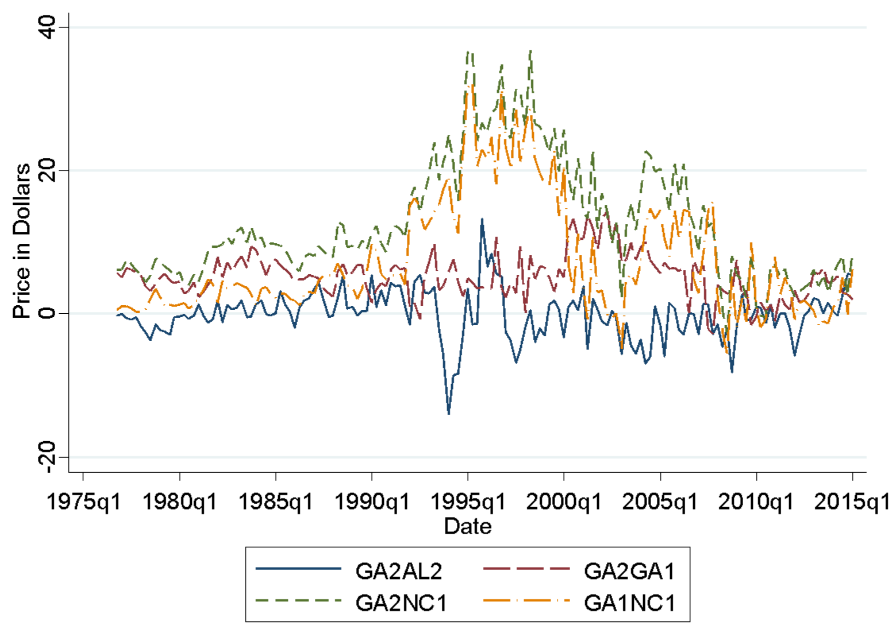

Figure 2.6: Pine sawtimber cross-region samples. Region is designated as two-letter State abbreviation and region 1 or 2; q1 = quarter 1.

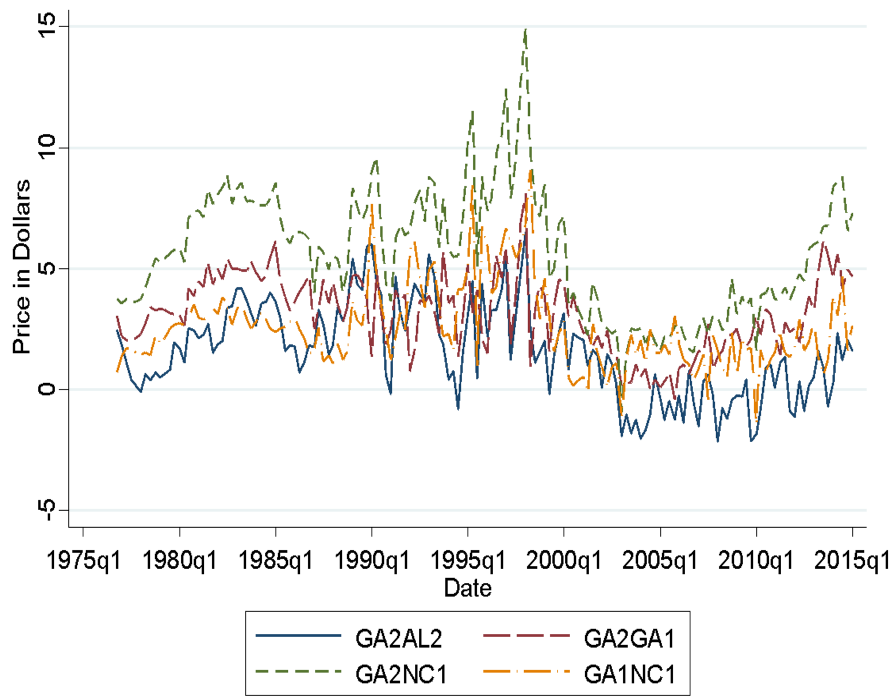

Figure 2.7: Pine pulpwood cross-region samples. Region is designated as two-letter State abbreviation and region 1 or 2; q1 = quarter 1.

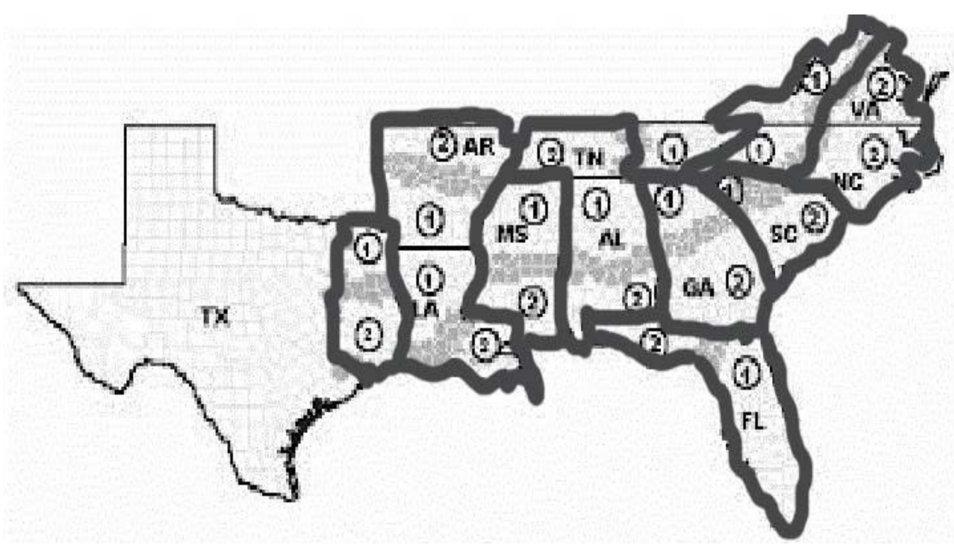

Figure 2.8: Pine sawtimber Clemente, Montañés, and Reyes innovative-outlier 2 breaks optimized for inclusiveness. Region is designated as two-letter State abbreviation and region 1 or 2; q1 = quarter 1.

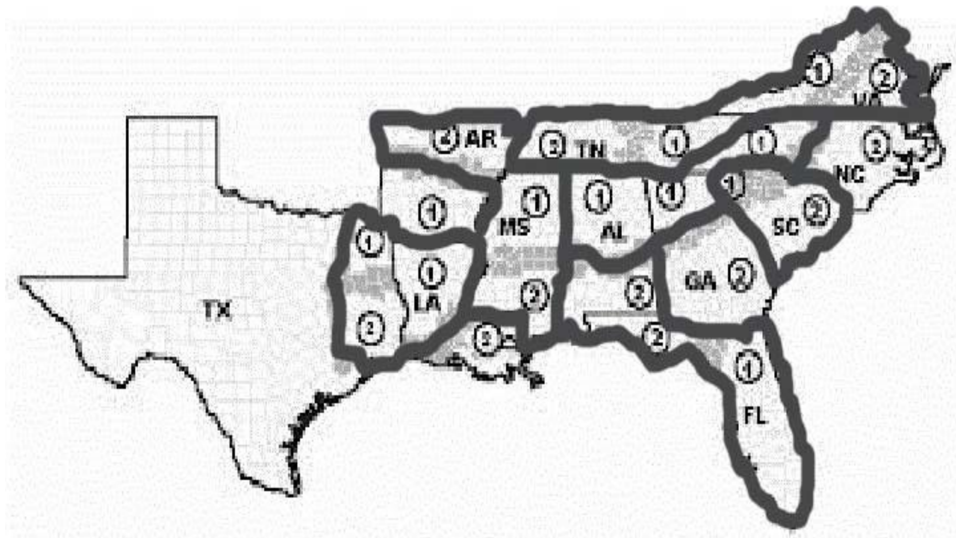

Figure 2.9: Pine sawtimber Clemente, Montañés, and Reyes innovative-outlier 2 breaks optimized by freight transportation. Region is designated as two-letter State abbreviation and region 1 or 2; q1 = quarter 1.

Figure 2.10: Pine pulpwood Clemente, Montañés, and Reyes innovative-outlier 2 breaks. Region is designated as two-letter State abbreviation and region 1 or 2; q1 = quarter 1.

CHAPTER 3

THE RELATION OF CHIP-N-SAW TO SAWTIMBER AND PULPWOOD PRICES: DIRECTION OF INFLUENCE[1]

Abstract

Relationships among prices of pine sawtimber (PST), pine pulpwood (PP), and chip-n-saw (CNS) were examined for southeastern markets in the United States. The data were extracted from the Timber Mart-South database and included quarterly prices of pine products from 1979 to 2015 for markets in Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, and Texas. The data were separated into two regions in each State. Both regions were used for Alabama, Florida, Georgia, Mississippi, and South Carolina, but only single regions were used for Arkansas, Louisiana, North Carolina, and Texas. The number of significant lags indicated by the Akaike information criterion varied between one and three for all markets, and those lags were used for further analysis. The Granger causality test using the Yamamoto–Toda method indicated significant predictability of PST by CNS in regions 1 of Alabama and Georgia and regions 2 of Mississippi and North Carolina; PST by PP in region 1 of Alabama and regions 2 of Georgia and North Carolina; CNS by PST in both regions of Alabama and Georgia and region 1 of Florida; CNS by PP in regions 1 and South Carolina and Texas and regions 2 of Alabama and Georgia; and PP by PST in regions 1 of Alabama and South Carolina. Predictability of PP by CNS was not significant in any region. The Granger causality test using a

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[1]Misztal M, Siry J, Harris T, Mei B, & Bowker M. To be submitted to *Forest Science*.

differencing method indicated significant predictability of PST by CNS in regions 1 of Georgia and Mississippi; PST by PP in region 2 of Georgia; CNS by PST in both regions of Alabama and Georgia, region 1 of Mississippi, and regions 2 of Florida and South Carolina; CNS by PP in region 1 of Texas and region 2 of Georgia; and PP by PST in both regions of Georgia, region 1 of Alabama, and region 2 of South Carolina. Based on the number of significant predictabilities, the strongest causality was for prediction of CNS by PST, and the weakest was for prediction of PP by CNS. Of all the regions, the highest number of significant causalities was in region 1 of Alabama and region 2 of Georgia; no causalities were significant in regions 1 of Arkansas and Louisiana.

Introduction

Lumber production in the Southeast surpassed the North and the West in 1989 and remains the top region in terms of production (Howard & Jones, 2016). Production specifics vary greatly throughout the region because of climate, ease of transportation, geography, proximity to ports, soil conditions, and many other factors. Chip-n-saw (CNS; ~8–11 inches in diameter at breast height) is a relatively new designation for timber product that lies between the more traditional designations of pulpwood (~6+inches in diameter at breast height and sawtimber (~12 inches or more in diameter at breast height). The CNS designation may result in downward pressure on prices for pine pulpwood (PP) and upward pressure on prices for pine sawtimber (PST) by absorbing what would otherwise be the top end of PP and the bottom end of PST. At various market times, CNS might be used as a substitute for either PP or PST. The exact nature of the relationships among those products can be of practical use for deciding on whether to delay harvest to have PP grow into CNS or CNS grow into PST.

Data from Timber Mart-South (TMS) contain 40 years of quarterly information from 11 States in the southeastern United States. The long-time period also includes distinct structural breaks in the market that significantly affected market behaviors across the region. Several previous studies used the TMS data to measure the relationships among prices across regions. Yin et al. (2002) examined PP and PST prices and found evidence of cointegration between geographically noncontiguous regions. Bingham et al. (2003) considered outside policy factors and found that price shocks were quickly disseminated across the coast to create one large market with two interior submarkets. Zhou and Buongiorno (2005) created a space-time autoregressive moving average model to which they apply impulse shocks. Price shocks took up to a year to disperse. Hood and Dorfman (2015) analyzed the dynamics of the TMS stumpage regions using an autoregressive model. Markets were linked at the peak of demand because of the housing boom but tended to segment as demand fell.

Besides spatial price relationships, other price relationships are of interest to forest owners and anyone trying to understand the market dynamics of the industry. Ning and Sun (2014) looked at vertical prices by examining three prices along the demand chain in the Southeast and West between 1977 and 2011. Both linear and threshold cointegration were used to model the relationship between stumpage and delivered prices and then between delivered prices and the lumber price of softwood. The South was more cointegrated then the West, and the first stage was more closely related than the second stage. Prices are more responsive with larger margins than with smaller ones. Nagubadi et al. (2001) examined hardwood pulpwood, mixed hardwood sawtimber, and oak sawtimber in six southeastern States. Little evidence of market integration was found across regions, with the least integration among pulpwood. Zhou and Buongiorno (2005) considered causality tests among southeastern PST and PP prices in relation to forest product prices for the United States including softwood lumber, paper, and wood pulp. They found no cointegration between any of the prices, but they did find evidence that southeastern sawtimber prices were Granger caused by national lumber prices. The lack of any causality in the pulpwood markets suggested that the southeastern pulpwood markets were noncompetitive. Because there was no long-term relationship between pulpwood and pulp products, Zhou and Buongiorno (2005) suggested that paper mills behave like monopsonists.

Research also has been conducted on the nature of prices and harvesting decisions. Mei et al. (2010) considered the volatility of southeastern prices in softwood sawtimber, softwood pulpwood, hardwood sawtimber, and hardwood pulpwood. They used weather conditions, industry capacity, and end product price volatility as independent variables. They found that softwood sawtimber was the most volatile in absolute terms and that capacity had the most explanatory power over volatility. Prestemon and Wear (1999) analyzed aggregated North Carolina stand-level data to measure the responsiveness to price over time as the vintages of inventory shift using a probit model. They found that higher sawtimber prices led to lower pulpwood production, higher pulpwood prices led to higher pulpwood production, and harvest timing was insensitive to price changes.

Parajuli and Chang (2015) analyzed the relationship between PST, CNS, and PP. Based on prices from the south-central United States, both PP and CNS prices were major covariates of sawtimber price. In addition, no bidirectional causality existed between any pair of forest product prices. An explanation was that harvesting PP and CNS were short-term decisions that influenced the more long-term decision-making processes of sawtimber. Landowners may use PP and CNS prices to predict PST prices.

The purpose of this chapter was to extend the research of previous studies to more markets and more time periods with additional focus on methodology to reduce possible bias associated with pretesting for cointegration and stationarity. The relationships among PP, CNS, and PST were analyzed in each State using cointegration (Johansen, 1995) and Granger causality (Granger, 1969). Cointegration implies a long-term connection, whereas Granger causality suggests a quicker short-term association. Although that interpretation is standard, it may be oversimplified because a long-term relationship may not always indicate a short-term relationship (Fugarolas et al., 2007). To test for Granger causality, a standard vector autoregression (VAR) model was developed with an augmented specification to eliminate pretest bias and lead to more robust results (Giles & Mirza, 1999).

Methods

Cointegration analysis allows testing whether markets follow the law of one price (LOP) and behave as one market (Uri & Boyd, 1990). Stationarity in the analysis can be determined using the augmented Dickey–Fuller (ADF) test (Dickey & Fuller, 1979). Results of the ADF test are sensitive to the number of lags which need to be determined on the basis of each individual series (Cheung & Lai, 1995). If the lag number is too small, serial correlation will remain and bias the test. If the number is too large, the test will lose power. Lags can be determined using the Akaike information criterion (AIC; Akaike, 1973), the Schwarz information criterion (BIC; Schwarz, 1978), or the Hannan–Quinn information criterion (HQIC). These criteria serve to suggest a starting number of lags which are then tested against serial correlation and significance to determine the best fit. The Johansen method (JH; Johansen, 1995) tests for cointegration over bivariate and multivariate series. More details about the cointegration analysis and the associated tests are presented in Chapter 2.

Granger causality (Granger, 1969) posits that z_t can be said to Granger cause x_t if x_t can be predicted better with the z_t process than without it. Another perspective is to consider the contrapositive of noncausality. If the information in the previous values of z_t do not help predict x_t, then z_t cannot be said to cause x_t. The possibility of consumers' expectations of future prices affecting prices today was ignored because modeling expectations require significantly stronger assumptions and complexity.

The Granger analysis uses both a basic and an augmented VAR model with specifications as defined by Toda and Yamamato (1995) and Dolado and Lütkepohl (1996), here called TYDL. The TYDL VAR model is expressed as

$$\begin{bmatrix} PST_t \\ CS_t \\ PULP_t \end{bmatrix} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \end{bmatrix} + \sum_{i=1}^{p} \begin{bmatrix} A_{11,i} & A_{12,i} & A_{13,i} \\ A_{21,i} & A_{22,i} & A_{23,i} \\ A_{31,i} & A_{32,i} & A_{33,i} \end{bmatrix} \begin{bmatrix} PST_{t-i} \\ CS_{t-i} \\ PULP_{t-i} \end{bmatrix} +$$

$$+ \sum_{j=p}^{p+m} \begin{bmatrix} B_{11,j} & B_{12,j} & B_{13,j} \\ B_{21,j} & B_{22,j} & B_{23,j} \\ B_{31,j} & B_{32,j} & B_{33,j} \end{bmatrix} \begin{bmatrix} PST_j \\ CS_j \\ PULP_j \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{bmatrix},$$

where λ_i are exogenous dummy variables (seasonality and breaks), *A* is a standard matrix of autoregressions, *B* is a matrix due to TYDL additional correctional lag, and *m* is the maximum order of the endogenous variables. Giles and Mirza (1999) consider the TYDL method as robust and State that although overfitting results may lead to a modest loss of efficiency, pretesting bias and inadequate lags can lead to "significant over rejections" (Giles & Williams, 2000). The standard VAR model is identical except that the *B* matrix is omitted. The VAR model may be misspecified with I(1) level price variables so first-differenced price variables are used. Pretesting for cointegration is also recommended and an error correction term, as seen in the

VECM, can be added to mitigate the long-term relationship between the two variables (Hamilton, 1994).

Granger causality is determined using a modified Wald test. A Wald test for a set of q-dimensional linear hypothesis $Rb = r$ tested jointly can be written as

$$w = (Rb - r)'RVR'(Rb - r)',$$

where b is the estimated coefficient vector and V is the estimated variance-covariance matrix (Judge et al., 1985). A chi-squared distribution with q degrees of freedom is used to determine significance levels; $m = 1$ because the maximum order of the endogenous variables is 1. The null hypothesis $H_0 = A_{kl,1} = A_{kl,2} = \ldots = A_{kl,p} = 0$, where k and l are one of PST, CS, or PP, implies that variable l does not cause variable k. For example, if $k = 1$ and $l = 2$, this suggests that CS does not cause PST. The causality tests are conducted using both the standard VAR and TYDL modified VAR.

Exogenous seasonal dummy variables were added without having to change the estimation procedure (Park & Phillips, 1989; Sims et al., 1990). Bauer and Maynard (2012) claim that the TYDL method is robust in this instance, even with extensions such as structural VARs with stochastic exogenous variables. In addition to controlling for seasons, dummy variables are included for structural breaks after 1992 and 2008, which were determined endogenously in Chapter 2.

Lag length is critical for correctly inferring Granger causality (Thornton & Batten, 1985). Choosing arbitrary lag lengths leads to contradictory results. The significant number of lags was initially evaluated using AIC, HQIC, and BIC while ignoring the additional TYDL lag ($m = 0$).

To verify that the lag length is optimal and that the model is tractable, a series of diagnostic tests were run. The Lagrange Multiplier (LM) test was used for autocorrelation among residuals in VAR (Johansen, 1995). The LM for any given lag is

$$\mathrm{LM} = (T - d - 0.5)\ln\frac{|\hat{\Sigma}|}{|\tilde{\Sigma}|}$$

where T is the number of observations and $\hat{\Sigma}$ is the maximum likelihood (ML) estimate of the variance-covariance matrix of the disturbances. $\tilde{\Sigma}$ is derived from an augmented VAR that uses a vector of $K \times 1$ residuals for K equations in the VAR as in Davidson and MacKinnon (1993). For each lag j, an augmented regression is run with the residuals lagged j times. $\tilde{\Sigma}$ is the ML estimate of the variance covariance matrix of the disturbances from this augmented VAR and d is the number of estimated coefficients. If there is evidence of autocorrelation, additional lags are added. To verify that the number of lags is not excessive, a Wald test is run to test that all endogenous variables at any given lag are jointly equal to zero for each equation. If the Wald test rejects the significance of the last lag in all cases, the number of lags is reduced. Often tests show nonnormality, kurtosis, and skewness of disturbances, but this is not an issue for Granger causality testing in VAR models (Johansen, 2006). Stability, which implies the effects of shocks fade over time, is verified by testing that the eigenvalues of the coefficient matrices have modulus less than 1 (Lütkepohl, 2005). Different numbers of lags between different combinations of products and across regions are expected (Comincioli, 1996). Ivanov and Kilian (2001) suggest that HQIC is the most accurate criterion for quarterly data with over 120 observations and BIC is better for those with fewer than 120 observations.

Accounting for seasons and structural breaks does not make a large difference in the Granger causality outcomes. Accounting for small samples and the degrees of freedom correction had a greater impact making the results less significant. A degree of freedom correction was used for small samples, which changes the ML factor of $1/T$ to $1/(t - m)$, where m is the average number of parameters in each equation.

Data

Data were provided by Timber Mart-South (TMS) and consisted of stumpage price data from 11 States. Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia each contain data from their inception in second quarter (2Q) of 1980 through the first quarter (1Q) 2016. Data are collected on individual timber sales from reporters in each region. The data are then checked, aggregated, and compiled by the staff at the Frank W. Norris Foundation. Each State is divided into two regions following a reorganization from three regions in 1Q 1991 (Prestemon & Pye, 2000). Each region will be identified by its two-digit State code followed by 1 or 2 denoting region number. Focus was on quarterly average prices of PST, CNS, and PP for each region. These are chosen because they are the most consistent in definition and the most complete over time. Stumpage prices are considered over delivered prices due to simplicity of concept and the perceived variability of transportation costs by region and over time (Hood & Dorfman, 2015). More data points are available for stumpage than delivered prices, and stumpage prices are more relevant to TMS and their subscribers.

Focus was on nominal level prices as suggested by Prestemon (2003). Real price data are also analyzed and resulted in similar findings, which are not reported. Usually, the natural log of prices is used for cointegration tests. The most common reason is that prices tend to grow exponentially over time. This was not true for either PST, CNS, or PP as seen in Figure 3.1. The logarithms of prices are also used when the data exhibits great variability, which is not the case in these data. Cointegration tests on natural logarithms of prices imply stronger interest in percent change in price rather than the price itself. Given that all regions use the same currency and that changes in price are likely to be equal in level across regions rather than proportional, log prices are not necessary. Regions with incomplete data of over two periods in a row (e.g., Virginia and Tennessee) were excluded from this study. In Texas and Louisiana, alternatives of using the combined regions to form a State were considered but are not reported in this paper.

Results

Table 3.1 shows the number of lags as indicated by several criteria and as used in subsequent analyses. The AIC tests indicate the highest lags, up to the 6th for MS2. The lags are smaller by HQIC and the smallest for BIC. The last test is regarded as the most useful one in Granger causality (Clarke & Mirza, 2006). Starting from lags indicated by BIC, the lag is increased sequentially until autocorrelations were eliminated. The number of lags used varied from one to four, with two being the most common.

Probabilities for Granger causality test in all regions with the TYDL correction are shown in Table 3.2. In general, only 20 out of possibly 84 combinations of region by causality type were statistically significant at the 5% level. No significant causalities are found in the five regions (AR1, FL1, LA1, MS1, and SC2). Four causalities were found in AL1, 3 in GA2, and 2 in AL2, GA1, and NC2. The most common causality is PST predicting CNS, occurring in 5 regions, followed by CNS predicting PST and PP predicting CNS, occurring in 4 regions. No significant causality was found for CNS predicting PP.

Contents of Table 3.2 are visualized in Figure 3.2. Only GA2 shows causality across the three directions. Only AL1 and NC2 show causality in two directions, with a single direction for

AL2, FL2, GA1, MS2, SC1 and SC2. Causality may be insignificant because of lack of power. After relaxing the significance level to $P < 0.2$, the most common causality is PP predicting PST, occurring in 10 out of 14 regions.

Table 3.3 shows the same probabilities as in Table 3.2 in a model without the TYDL correction. The results are visualized in Figure 3.3 with corrections for pretesting bias. For most regions, the significant causalities did not change. One causality was removed from GA1 and MS1, one causality was added to GA2, and two causalities were added to NC2. TYDL can suffer from inefficiency in small samples because of overfitting (Toda & Yamamoto, 1995). It is used because it is not dependent on the level of integration or cointegration.

Table 3.4 shows the results of the JH cointegration tests for each State. All three products with every binary combination of products are considered. Cointegration suggests Granger causality in at least one direction. Granger causality in both directions implies cointegration. Ideally, any cointegrating vectors in case of all three products would show up in one of the pairings and the total number of cointegrating vectors in binary grouping would add up to the three-product case. There are several reasons for this reasoning to hold up. For instance, like with Granger causality, there may be a relationship between two products which is only evident when the complete system is tested. Texas is the only State with two binary relationships although it shows every binary relationship to be cointegrated. This would suggest full rank and should not be possible with I(1) price series. GA2 having a binary cointegrating vector that is not reflected in the three-product VAR is puzzling. This suggests inconsistencies across tests and a fundamental contradiction as to whether the data are nonstationary.

Discussion and Conclusions

The cointegration results did not appear to directly support the Granger causality results. Any cointegrated pair should have at least one Granger causality link, if not both, although this may not always be the case (Fugarolas et al., 2007). Granger results were trusted over the cointegration results for a number of reasons. Chapter 2 determined that the TMS data contain strong evidence of structural breaks. These were not taken into account here due to the non-bivariate nature of the data. Secondly, the cointegration results are not consistent within themselves when comparing the binary parings to the three products simultaneously. Thorough estimation is done using multiple lags in each case to make sure lag order was not misspecified. Finally, Granger causality is a more straightforward and more robust method that bypasses the need to account for order of cointegration. Cointegration analysis is sensitive to many different issues that arise from ill-behaved data (Johansen, 2006).

The results in this paper can be compared with those of Parajuli and Chang (2015) for TX and AR markets. They found unidirectional causality from PP and CNS to PST. In this study, overall the most prevalent trend was towards PST influencing CNS. However, it seemed that many divergent patterns emerged region to region as seen in Figure 3.2. This shows the unique aspects of each market.

The similarities between the TYDL results and the standard results suggest that the overall analysis is robust. The changes include finding influence of CNS and PP on PST in NC2 and double causality in between PST and CNS in GA1 and AL1. These two have similar characteristics and neighbor each other.

This paper shows the importance of understanding the particulars of each TMS region, which is crucial for anticipating regional variations. It also sheds light on the subjectivity of pine designation in the southeastern United States. It is one of the few forested regions in the world that has no legal conventions when it comes to evaluating stumpage. The designation is decided between the buyer and the seller and can vary from mill to mill or even sale to sale and there is constant overlap.

MS2 has had relatively large timber inventory with a high site index suitable for high value products such as poles and veneer quality lumber. This would lead to skimming into what would be sawtimber in other regions. The resultant sawtimber would be of lower value and may lead to it being bunched into CNS rather than reporting poor prices for smaller diameter PST.

GA2 has PP drawing both CNS and PST. This might be due to the relative weight of pulpwood in the GA2 lumber industry relative to the other two. With many plantations designed for pulpwood, it dominates the market. The market is very fluid and unlike other markets, PP drives the market rather than being a byproduct. Further, the prices for PST and CNS are likely influenced by GA2, for which the products are very closely tied together.

Other factors may include large land holdings and strong market presence by a particular company. Companies like this would be able to wait out market abnormalities. On the other hand, if timber investment management organizations (TIMOs) or real estate investment trusts (REITs) dominate, then steady revenue from land holdings is a priority. AL1 has relatively light manufacturing. AR1 has many plants, but they are relatively small, which leads to a fractured market. Conditions like these influence the cost of pine pulpwood and should be considered.

Given the significant changes in the industry and market, further study could be made into the changing nature of the causality. Unfortunately, the current data suffer from significant small sample problems when split in half. Both regions of Arkansas tend to fail the eigenvalue stability condition and tend to suffer from autocorrelation issues even at with a high number of lagged variables. The next step in analysis would be to combine overlapping markets. As shown in chapter 2, although sawtimber and pulpwood markets tend to overlap, regional markets are not identical. By combining well-identified markets, it is possible to see causality across regions and across products.

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Table 3.1: Numbers of lags indicated by different criteria and used for analysis after adjusting for autocorrelation by region

	Information criterion[2]			
Region[1]	Akaike	Hannan–Quinn	Schwarz	Used for analysis
AL1	5	3	1	3
AL2	3	1	1	1
AR1	3	2	2	1
FL1	2	2	2	2
FL2	2	2	1	2
GA1	2	2	1	2
GA2	2	2	1	3
LA1	1	1	1	1
MS1	3	3	1	4
MS2	6	2	2	3
NC2	2	1	1	1
SC1	2	2	2	2
SC2	1	1	1	1
TX1	1	1	1	2

[1]Region is designated as two-letter State abbreviation and region 1 or 2.

[2]All models tested for stability (stationarity) and autocorrelation.

Table 3.2: Probabilities[1] of Granger causality for product prediction[2] using the Yamamoto–Toda method with augmented vector autoregression as defined by Toda and Yamamato and by Dolado and Lütkepohl by region

	PST predicted by			CNS predicted by			PP predicted by		
Region[3]	CNS	PP	CNS and PP	PST	PP	PST and PP	PST	CNS	PST and CNS
AL1	0.02*	0.05*	0.00**	0.05*	0.24	0.03*	0.01**	0.49	0.02*
AL2	0.46	0.17	0.22	0.00**	0.04*	0.00**	0.43	0.22	0.47
AR1	0.78	0.15	0.32	0.22	0.77	0.47	0.07	0.93	0.17
FL1	0.27	0.21	0.27	0.22	0.72	0.47	0.93	0.51	0.78
FL2	0.75	0.09	0.26	0.08**	0.13	0.00**	0.90	0.32	0.64
GA1	0.03*	0.62	0.10	0.01*	0.62	0.03*	0.13	0.51	0.18
GA2	0.08	0.02*	0.01*	0.01**	0.02*	0.00**	0.12	0.46	0.20
LA1	0.80	0.44	0.68	0.42	0.67	0.58	0.84	0.95	0.98
MS1	0.69	0.84	0.84	0.19	0.09	0.04*	0.78	0.61	0.87
MS2	0.01*	0.05	0.01*	0.11	0.08	0.02*	0.56	0.12	0.28
NC2	0.02*	0.03*	0.02*	0.12	0.85	0.28	0.22	0.23	0.12
SC1	0.86	0.18	0.22	0.77	0.01*	0.05*	0.04*	0.05	0.02*
SC2	0.58	0.19	0.43	0.37	0.10	0.21	0.48	0.41	0.68
TX1	0.52	0.15	0.34	0.16	0.01*	0.00**	0.67	0.49	0.67

[1]* denotes 5% significance, and ** denotes 1% significance.

[2]CNS = chip-n-saw, PST = pine sawtimber, and PP = pine pulpwood.

[3]Region is designated as two-letter State abbreviation and region 1 or 2.

Table 3.3: Probabilities[1] of Granger causality for product prediction[2] using the Yamamoto–Toda method without augmented vector autoregression as defined by Toda and Yamamato and by Dolado and Lütkepohl by region

	PST predicted by			CNS predicted by			PP predicted by		
Region[3]	CNS	PP	CNS and PP	PST	PP	PST and PP	PST	CNS	PST and CNS
AL1	0.09	0.07	0.00**	0.01*	0.38	0.02*	0.02*	0.48	0.10
AL2	0.80	0.11	0.23	0.00**	0.13	0.00**	0.24	0.09	0.22
AR1	0.38	0.37	0.47	0.09	0.54	0.23	0.26	0.88	0.61
FL1	0.06	0.31	0.12	0.65	0.54	0.79	0.94	0.35	0.61
FL2	0.29	0.09	0.17	0.03*	0.12	0.01**	0.95	0.92	0.99
GA1	0.03*	0.38	0.10	0.00**	0.26	0.00**	0.04*	0.57	0.04*
GA2	0.70	0.03*	0.03*	0.00**	0.01*	0.00**	0.02*	0.66	0.04*
LA1	0.99	0.59	0.86	0.70	0.69	0.89	0.75	0.83	0.92
MS1	0.65	0.57	0.76	0.03*	0.05	0.01**	0.68	0.09	0.29
MS2	0.01**	0.05	0.01**	0.12	0.05	0.02*	0.71	0.08	0.26
NC2	0.11	0.25	0.09	0.32	0.71	0.63	0.36	0.68	0.38
SC1	0.99	0.15	0.26	0.13	0.17	0.11	0.18	0.28	0.30
SC2	0.37	0.12	0.28	0.02*	0.23	0.06	0.04*	0.88	0.88
TX1	0.86	0.75	0.91	0.07	0.00**	0.00*	0.22	0.55	0.44

[1]* denotes 5% significance, and ** denotes 1% significance.

[2]CNS = chip-n-saw, PST = pine sawtimber, and PP = pine pulpwood.

[3]Region is designated as two-letter State abbreviation and region 1 or 2.

Table 3.4: Johansen cointegration for products[1] using the Pantula principle and 5% trace test

	Rank			
Region[2]	PST, CNS, PP	PST, CNS	PST, PP	CNS, PP
AL1	1	1	0	1
AL2	1	0	0	0
AR1	1	0	0	0
FL1	0	0	0	0
FL2	1	1	0	0
GA1	0	1	0	0
GA2	1	0	0	0
LA1	1	0	0	0
MS1	1	1	0	0
MS2	0	1	0	0
NC2	0	0	0	0
SC1	1	1	0	0
SC2	1	0	0	0
TX1	2	1	1	1

[1]PST = pine sawtimber, CNS = chip-n-saw, and PP = pine pulpwood.

[2]Region is designated as two-letter State abbreviation and region 1 or 2.

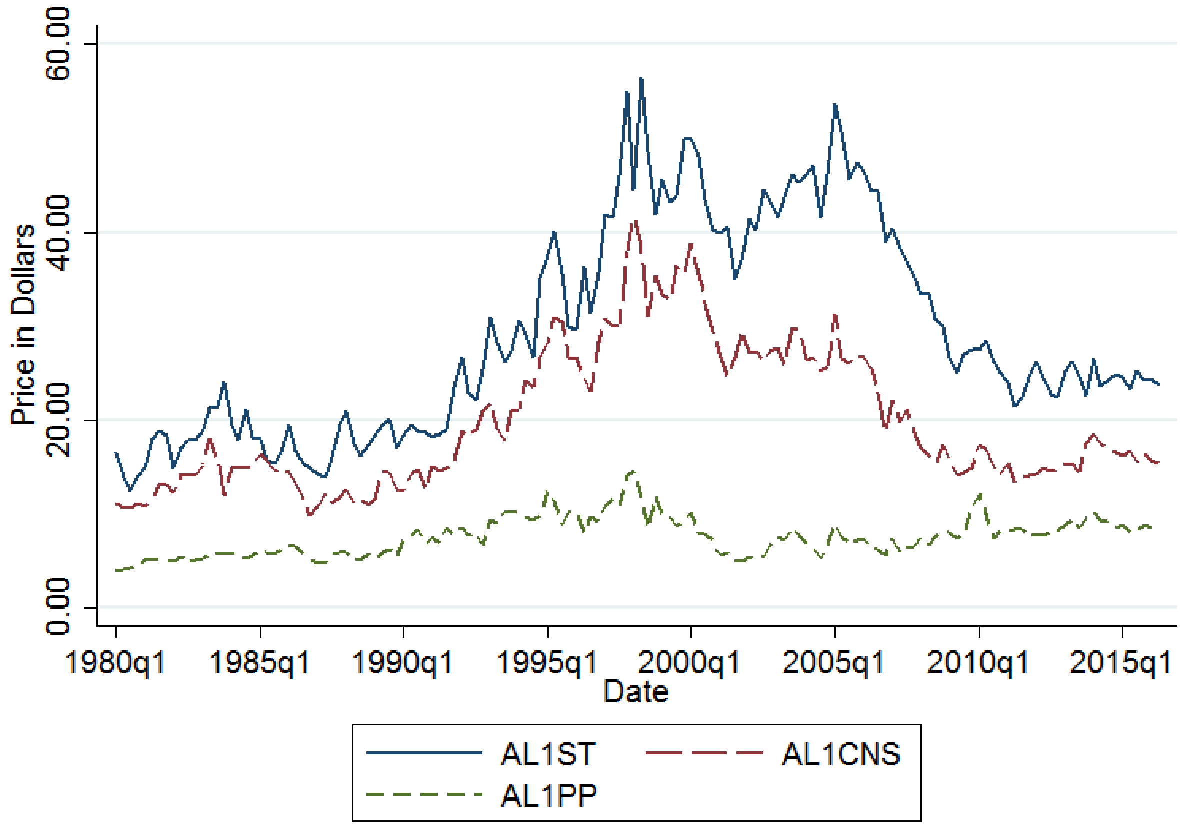

Figure 3.1: First-quarter prices of pine sawtimber, chip-n-saw, and pine pulpwood in region 1 of Alabama by year. q1 = first quarter, ST = pine sawtimber, CNS = chip-n-saw, and PP = pine pulpwood.

Figure 3.2: Causality at the 5% level using the Yamamoto–Toda method with augmented vector autoregression as defined by Toda and Yamamato and by Dolado and Lütkepohl.

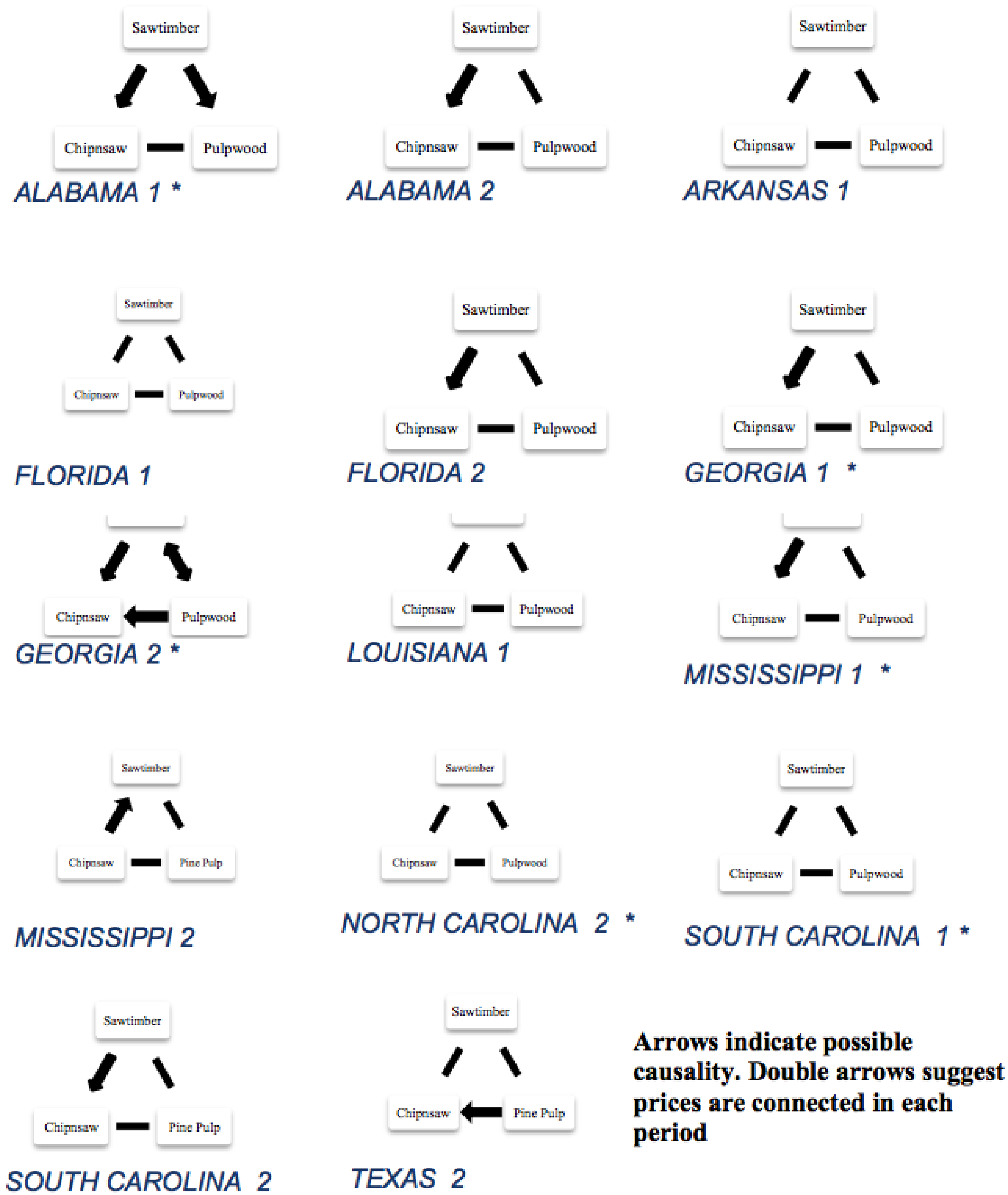

Figure 3.3: Causality at the 5% level using the using the Yamamoto–Toda method without augmented vector autoregression as defined by Toda and Yamamato and by Dolado and Lütkepohl; * indicates differences between models with and without augmented vector autoregression.

CHAPTER 4

CAUSES AND RELATIONSHIPS BETWEEN PINE DELIVERED AND STUMPAGE PRICES IN THE U.S. SOUTH[1]

Abstract

Data included quarterly pine stumpage and delivered prices across 11 States in the southeastern United States were divided into two regions. The first analysis used Granger causality to determine whether stumpage prices were determined by delivered prices or the reverse. Granger causality tests accounted for or ignored breaks and seasons. For pine sawtimber (PST), 32% of regions had significant delivered-to-stumpage causality, and 82% had stumpage-to-delivered causality regardless of whether or not breaks and season were considered. For pine pulpwood (PP), similar percentages were obtained if breaks and season were ignored, but the percentages decreased to 27% and 36%, respectively, if breaks and season were considered. Effects of other factors on stumpage and delivered prices and their differences were determined for southern Georgia, the largest region. None of the factors were significant for all prices. Mining/logging wages and midwestern housing starts were significant for stumpage and delivered prices. Industrial production and average hourly construction wage were significant for differences between stumpage and delivered prices. Industrial production was significant for delivered but not stumpage prices. In contrast, the 10-year treasury rate was significant for stumpage but not significant for delivered prices. Delivered prices generally affected stumpage prices more;

[1]Misztal M, Siry J, Harris T, & Bowker M. To be submitted to *Canadian Journal for Forest Research*.

however, causality was dependent on season and breaks. In general, various factors affect stumpage and delivered prices and their difference separately for PST and PP.

Introduction

Stumpage price is the price paid to a landowner to harvest marketable trees on a given piece of land (Nieuwenhuis, 2010). Delivered price is the price paid to a logger at the gate of the mill. Logging margins are defined as differences between delivered and stumpage prices. Variations in stumpage prices are different from delivered prices because of specifics of the harvest area: incline on which the trees grow, distance from lumber mill, road quality to lumber mill, constancy of product, logging cost, skidding, hauling, and the opportunity cost of capital, insurance, and any other cost associated with getting the appropriate product to the appropriate mill. Loggers are independent agents that contract with landowners and mills separately. Their major costs are fuel for trucks and machinery, labor, maintenance, and repair as well as the cost of the machinery itself and depreciation. They tend to operate in small groups of less than 10 on a job, although the capital involved can differ greatly (Baker et al., 2014). To make a profit, loggers must correctly price the stumpage and the cost of harvesting and delivering the wood. If they underestimate the cost, they will lose money on the haul. The availability of appropriate timberland and the degree of competition among mills also plays a part.

Sun and Zhang (2006) analyzed timber harvesting margins in the southern United States between 1977 and 2001. They reported that real growth rate of harvesting margins was negative for pine pulpwood (PP) but positive for pine sawtimber (PST), hardwood pulpwood, and hardwood sawtimber. Harvesting margins for pulpwood were more stable over time and more integrated spatially than for sawtimber, which could be explained by changing demand and industry structure. Ning and Sun (2014) looked at timber harvesting margins for timber and lumber markets. For example, earlier prices (stumpage/delivered) were correlated with stronger integration in later prices (delivered/lumber price). The West had less market cointegration than did the South.

The purpose of this chapter was to analyze differences between delivered and stumpage prices using data from Timber Mart-South (TMS). First Granger causality with breaks and season ignored or accounted for was used for PST and PP in 11 States. Then effects of other factors such as wages, housing starts, and fuel prices were examined for southern Georgia, the largest region (Mendell, 2006).

Methods

Direction of causality between prices was determined using Granger causality and limited cointegration methods Johansen method for pairs (Johansen, 1995). Analyses controlled for seasonality and structural breaks by including dummy variables for seasons and for endogenously found breaks (Johansen, 2006).Optimal lags were determined using the Schwarz information criterion (Schwarz, 1978) although the Akaike information criterion (Akaike, 1973) and Hannan–Quinn information criterion (HQIC) were used and each possible lag was checked for goodness of fit, significance of lags, presence of autocorrelation to verify a sound vector auto-regression (VAR) model. The significance test for Granger causality used a standard Wald test. The methods were more comprehensively described in the methods sections of the second and third chapters. To test for Granger causality, a standard VAR model was derived as well as an augmented specification that eliminates pretest bias and leads to more robust results (Giles & Mirza, 1999).

Although causality analyses provide a statistical indication of the direction of causality, they do not indicate which factors influence that causality. Those factors can be determined by direct regression on prices. Production factors that influence the price of stumpage, delivered and logging margins were considered for both PST and PP. According to (Baker et al., 2014) the four largest components affecting logging companies are labor, fuel and oil, depreciation, and repair and maintenance. This paper uses proxy variables for these costs to establish the significance of each cost with respect to logging margins as well as delivered and stumpage prices separately. Each was regressed on a series of aggregated variables. Given that the data available are not specific to the region or to logging, the coefficients are less important than the significance of the value.

Data

The TMS stumpage and delivered wood prices from 11 States were analyzed. Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia each contain data from their inception in Fourth Quarter (4Q) of 1976 through the first quarter (1Q) 2016. Data are collected on individual timber sales from reporters in each region. The data are then checked, aggregated, and compiled by the staff at the Frank W. Norris Foundation. Each State is divided into two regions following a reorganization from three regions in 1Q 1991 (Prestemon & Pye, 2000). In this paper, each region will be identified by its two-digit State code followed by 1 or 2 denoting region number. Focus was on quarterly average prices of stumpage and delivered prices for PST and PP for each region. These are chosen because they are the most consistent in definition and the most complete over time. Stumpage prices are used rather than delivered prices due to simplicity of concept and the perceived variability of transportation costs by region and over time. They are also more frequently reported.

As suggested by Prestemon (2003) to account for the unique conditions of this market, the focus was on nominal level prices. Real price data are also analyzed and resulted in similar findings, which are not reported. Usually, the natural log of prices is used for cointegration tests. The most common reason is that prices tend to grow exponentially over time. This was not true for either PST or PP which maintain the same price gain over the considered time period. In most cases the logging margin tend to diverge in 2008, which may imply greater market power of the mills in relation to the loggers. Many States also exhibit price spikes towards the end of the 1990's for both stumpage and delivered timber. The logarithms of prices are also used when the data exhibits great variability, which is not the case in these data. Cointegration tests on natural logarithms of prices imply stronger interest in percent change in price rather than the price itself. Given that all regions use the same currency and that changes in price are likely to be equal in level across regions rather than proportional, log prices are not necessary.

The Federal Reserve Economic Research supported by the St. Louis Federal Reserve (https://fred.stlouisfed.org) provided the economic indicators that could serve as proxies for the major factors in logging and logging demand found in the literature. Included are wages for mining/logging as well as wages for average hourly wage for production and for construction. Production wages serve as a control for mill wages, whereas construction is tied to housing starts and seasonal and skilled labor. Housing starts for the Southeast, West, Northeast, and Midwest are included. The producer-price index (PPI) for agricultural machinery is used to account for inflation as well as a proxy for buying capital machinery. Industrial production works similarly. For depreciation, the 10-year interest rate is used to represent the cost of borrowing. Finally, the price of diesel (called Diesel 2) is used to account for the changing cost of fuel. The prices were analyzed by a linear model $y = Xb + e$, where y is a vector of prices, b is a vector of the effect of economic indicators, e is a vector of residuals assuming an IID, and X is a design matrix relating y to b. As the value of b is relative to the scale of indicators, only the significance of each indicator was tested.

Results

Table 4.1 presents Granger causality for PST either ignoring (basic) or accounting (control) for breaks and seasons. Out of 22 regions, basic causality indicated that 19 regions had a significant causality of stumpage causing delivered prices, whereas the reverse causality was significant in only 7 regions. Control causality was almost identical showing that causality for PST is robust with regard to seasons and breaks. AR1 is the only region where delivered prices influence stumpage. AL1, GA2, LA2, SC1, VA1 and VA2 show a possible long-term relationship between both prices influencing one another.

In the basic model, which does not control breaks or seasons, the lags vary from one to six. In general, larger lags tend to indicate less data. In several cases, (FL1, LA1, SC1 and TX1), there are large differences between the regions within States. The number of lags seems to be negatively correlated with mill capacity (Mendell, 2006). Regions with less capacity, and therefore containing less data, tend to require higher lags to fit the model. AR2, NC1, TX1, and VA1 are best fitted with over four lags and have relatively lower PST capacity (Mendell, 2006).

In all but 3 of 22 markets, PST stumpage prices seem to impact delivered prices. In seven markets, delivered prices also Granger cause stumpage prices, which suggests that these prices are mutually reinforced. Some of the interlinked prices are for GA2 and AL1.

The second part of analyses (control) accounted for structural breaks and seasons. In general, the number of lags was similar between the control and the adjusted data but with smaller differences between the regions in TX. The control model confirms stumpage driving delivered prices. AR1 is the one region where the causality is reversed. In SC1 and LA2, the prices seem interlinked. In FL1, FL2, and NC1 they seem to be decoupled. None of these are significantly large PST markets. The significance level for stumpage cases delivered is generally higher, indicating some but not critical importance in accounting for breaks and seasons.

Statistics of causality for PP are presented in Table 4.2. Results of basic casualties are almost reverse of those of PST, where only 8 regions had a significant causality of stumpage causing delivered prices, whereas the reverse causality was significant in 17 regions. Control causality was quite different: six regions had a significant causality of stumpage causing delivered prices, whereas the reverse causality was significant in only nine regions. Subsequently, causality for PP is affected by seasons and breaks. In general, FL1, GA1, LA2, NC1, TX1, TX2, and VA2 show the influence going from stumpage to PST. Both regions of TX and NC1 show a long term cointegrating relationship, although they also are relatively small markets. Delivered prices tend to impact future stumpage prices specifically in AR1, FL2, LA1, NC1, TX1, and TX2.

Lags in basic analyses are generally more uniform than for PST, whereas the lags are smaller for control. In basic, delivered causes stumpage is, in general, more significant than the stumpage causes delivered, but in control, many levels of significance change. Both mean that accounting for breaks and season is more important for PST than for PP or that PP prices are more affected by breaks and seasons. In a study on using combined data from all southeastern

States, the optimal lag for stumpage and delivered lumber price varied between 2 and 3 (Ning & Sun, 2014).

As a typical example of a healthy timber market and producer, GA2 was chosen as a sample market for more detailed analyses. In 2006 (Mendell, 2006), GA2 was the leading pine region in pulpwood demand and number of both pulpmills and sawmills. It was second in sawmills. Figures 4.1 and 4.2 show PST and PP prices for stumpage and delivered. In general, the prices follow each other although the spread for PP is much larger.

Table 4.3 shows significance of several factors on stumpage and delivered prices, and their difference for both PST and PP. When considering the logging margins for PST, PPI of agricultural machinery, average hourly wage of construction, and the Federal funds rate were significant at the 5% level, with only wages being significant at the 1% level. For PP, all but PPI were significant and so were diesel and housing in the Northeast, all well beyond the 1% level. PST shows both stumpage and delivered prices significant at the 1% level for all wages, fuel, and southern housing starts and 5% significance for midwestern housing starts. PP had significance in logging wages, northeastern and midwestern housing starts, and agricultural machinery. Production labor and fuel have a significant effect on the price of stumpage, whereas delivered prices had statistically significant relationship to skilled labor and industrial parts.

Discussion and Conclusions

TMS collects data that discount specific loads from premiums paid for long distances or difficult conditions. The mill price is supposed to be the standard price for local lumber, and additional premiums due to delivery distance, for example, are not included in the price reported. Stumpage prices may be biased downwards mainly due to premiums for large harvest areas and the permission to clearcut. The mill typically has a contract with each logger for a specified price per product and will manipulate to discourage products they don't need and encourage ones they need to continue to operate. Bonuses for reaching quotas are increasingly popular leading to market inefficiencies. The industry has changed from monopsonistic with one firm buying every type of wood in their vicinity to a more diversified buyers' market. Now different types of wood products from the same logger may go to different companies, not just different mills.

Stumpage tends to drive PP delivered price. With PST, there is less impact compared with PP. There are two theories that would explain these interactions that cannot be proven or disproven using current data and methodology. One is pricing information as suggested in Parajuli and Chang (2015). Given the higher value of PST and its increased relative volatility, landowners are more willing to wait until they get acceptable price signals. PP may not warrant as much research into price trends and the prices are more likely to vary based on distance and logging conditions (Grebner et al., 2013). The second is bargaining power. Considering PST as a premium product, land-owners may have more market power to influence the price. There are fewer substitutes, and the mills lose money if there is a supply shortage. On the other hand, PP sellers may be price takers. Their reasons to sell are more likely to not be from outside causes or as a byproduct of a different decision. Sun and Zhang (2006) looked at timber harvesting margins using the TMS data from 1977 to 2001. They explained differences for PP and PST as the result of demand dynamics for timber products. The results of Sun and Zhang (2006) differ from those of this paper as they found a significant pattern, but this paper does not.

Logging margins can be said to serve as a proxy for determinants of the logging companies. Both PST and PP had stand-ins for cost of machinery and its repair, wages, and interest rates as significant factors, which would be expected and is consistent with previous studies (Lang et al., 2016). PP was also sensitive to skilled wages, diesel, and housing starts in the northeastern United States. Significance of diesel fuel and production wages suggests that increases in transportation and management costs are especially significant on low margin products. It is also possible that there is more bargaining power for PST and they are able to pass on these two costs to the mills. Given that delivered and stumpage for PST were identical in which terms were significant, this further lends credibility to theory of the stronger bargaining power. Local housing starts also suggest that PST served mostly southeastern markets. PP served mostly midwestern and northeastern markets, suggesting it may have been easier to transport PP and consume it near those industrial centers into products that were more expensive to transport. In addition, the lower price margin may explain certain factors that are not passed on by the loggers and taken by the landowners. Fuel and production labor were of greater concern during the logging process, whereas more skilled labor and industrial parts factored into the prices the mills were willing to pay.

Detailed quantity information would allow for the calculation of price elasticity to better understand the relationship between buyers and sellers. (Mas-Colell et al., 1995). It would also allow a better understanding of how market conditions have changed over time. The dominance of hardwood or pine in any region is likely to play a part in the dynamics between loggers and mills in each region. There is also anecdotal evidence that loggers have become more diverse in their mill deliveries. Finally, the influence of one price on the other might be explained by market power or asymmetric information or another decision-making factor. Surveys of logging crews could shed more light into the mechanics of the relationship between delivered and stumpage prices.

For PST, evidence of causality of stumpage on delivered prices was significantly greater than the other way around. Seasonality and structural breaks were not significant factors. For PP, the causality direction was reversed, which suggests that delivered prices influence stumpage prices rather than the other way around. Controlling for seasonality and structural breaks was important for PP. Proxies for input prices for logging suggested that wages and interest rates were significant for logging margins for PST and PP, but diesel prices were significant only for PP. Delivered and stumpage prices for PST had very similar significant inputs, but diesel and agricultural machinery prices were significant only for delivered prices for PP.

It could be concluded that PP is an inferior good because there is a consistent supply from land owners that do not invest in silviculture and/or that harvest based on secondary needs. By contrast, high quality PST can usually only be produced with long term strategic thinking and investment. These results may imply that pulpwood is a secondary concern while PST is more of an investment. PST is an investment while PP is more of a byproduct from other harvests. These results suggest that prices are more time-sensitive to PP than to PST.

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Table 4.1: Pine sawtimber Granger causality[1] by region

	Basic[3]				Control[4]			
Region[2]	Lag	Rank	Delivered price causes stumpage price	Stumpage price causes delivered price	Lag	Rank	Delivered price causes stumpage price	Stumpage price causes delivered price
AL1	2	0	0.01*	0.05*	1	1	0.00**	0.00**
AL2	2	2	0.10	0.03*	2	2	0.12	0.025*
AR1	5	0	0.38	0.00**	5	0	0.00**	0.51
AR2	4	0	0.60	0.01	3	0	0.72	0.00**
FL1	4	1	0.01**	0.00**	5	0	0.11	0.01*
FL2	1	1	0.00**	0.02*	1	2	0.35	0.00**
GA1	3	0	0.50	0.00**	2	1	0.14	0.00**
GA2	3	0	0.04*	0.00**	2	0	0.03*	0.00**
LA1	4	0	0.55	0.00**	4	0	0.59	0.00**
LA2	1	2	0.21	0.02*	1	2	0.03*	0.00**
MS1	3	0	0.79	0.10	2	0	0.11	0.02*
MS2	3	0	0.17	0.02*	1	2	0.22	0.06
NC1	6	0	0.02*	0.03*	3	1	0.07	0.00**
NC2	3	1	0.53	0.00**	2	1	0.05	0.00**
SC1	4	0	0.09	0.01*	2	1	0.00**	0.00**
SC2	1	1	0.21	0.15	1	1	0.07	0.07
TN1	2	2	0.72	0.00**	3	2	0.37	0.00**
TN2	1	2	0.40	0.00**	1	2	0.68	0.00**
TX1	1	2	0.27	0.03*	1	2	0.99	0.01*
TX2	5	1	0.13	0.01**	1	0	0.25	0.13
VA1	5	1	0.00**	0.00**	5	1	0.00**	0.00**
VA2	1	2	0.02*	0.00**	1	2	0.02*	0.00**

[1]* denotes 5% significance, and ** denotes 1% significance.

[2]Region is designated as two-letter State abbreviation and region 1 or 2.

[3]Vector autoregression without dummy variables for breaks and seasons.

[4]Controls for breaks and seasons.

Table 4.2: Pine pulpwood Granger causality[1] by region

Region[2]	Basic[3] Lag	Basic[3] Rank	Basic[3] Delivered price causes stumpage price	Basic[3] Stumpage price causes delivered price	Control[4] Lag	Control[4] Rank	Control[4] Delivered price causes stumpage price	Control[4] Stumpage price causes delivered price
AL1	2	0	0.04*	0.39	…	0	0.10	0.37
AL2	3	1	0.01*	0.92	1	1	0.07	0.18
AR1	3	1	0.01*	0.97	4	1	0.00**	0.87
AR2	3	1	0.02*	0.51	1	1	0.45	0.72
FL1	3	0	0.13	0.30*	3	0	0.19	0.02*
FL2	4	0	0.02*	0.89	4	0	0.03*	0.13
GA1	3	0	0.04*	0.13	3	0	0.12	0.03*
GA2	3	0	0.44	0.61	2	0	0.21	0.60
LA1	3	1	0.02*	0.02*	1	2	0.02*	0.38
LA2	3	1	0.02*	0.02*	1	2	0.09	0.03*
MS1	7	0	0.02*	0.63	1	0	0.51	0.59
MS2	3	0	0.23	0.97	3	0	0.75	0.61
NC1	4	0	0.00**	0.20	4	0	0.02*	0.05*
NC2	1	1	0.00**	0.01**	1	1	0.34	0.05*
SC1	5	0	0.16	0.03**	4	0	0.58	0.04*
SC2	4	0	0.02**	0.12	3	0	0.20	0.19
TN1	1	1	0.00**	0.14	1	1	0.08	0.24
TN2	3	…	0.29	0.19	3	…	0.51	0.38
TX1	4	0	0.00**	0.00**	2	2	0.00*	0.00**
TX2	2	2	0.00**	0.03*	2	2	0.02*	0.03*
VA1	2	0	0.01**	0.11	2	0	0.10	0.19
VA2	1	1	0.00**	0.00**	2	1	0.43	0.01**

[1]* denotes 5% significance, and ** denotes 1% significance.

[2]Region is designated as two-letter State abbreviation and region 1 or 2.

[3]Vector autoregression without dummy variables for breaks and seasons.

[4]Controls for breaks and seasons.

Table 4.3: Significance[1] of prediction factors for pine sawtimber and pine pulpwood

	P > |Z| for pine sawtimber			*P* > |Z| for pine pulpwood		
Prediction factor	Difference	Stumpage	Delivered	Difference	Stumpage	Delivered
Mining/logging wages	0.50	0.00**	0.00**	0.10	0.00**	0.00**
Housing starts						
Southeast	0.21	0.00**	0.00**	0.08	0.48	0.47
West	0.11	0.14	0.47	0.60	0.37	0.19
Northeast	0.39	0.09	0.19	0.00**	0.00**	0.00**
Midwest	0.42	0.02*	0.03*	0.09	0.00**	0.00**
Agricultural machinery producer price index	0.00**	0.00**	0.00**	0.26	0.00**	0.00**
Industrial production	0.00**	0.80	0.05*	0.00**	0.79	0.01**
Average hourly wage						
Production	0.20	0.01**	0.00**	0.00**	0.00**	0.71
Construction	0.00**	0.01*	0.00**	0.00**	0.13	0.00**
10-year Treasury constant maturity rate	0.01*	0.02*	0.25	0.39	0.06	0.26
No. 2 diesel fuel prices	0.10	0.00**	0.00**	0.00**	0.00**	0.23
Constant	0.86	0.17	0.12	0.00**	0.39	0.00**

[1]* denotes 5% significance, and ** denotes 1% significance.

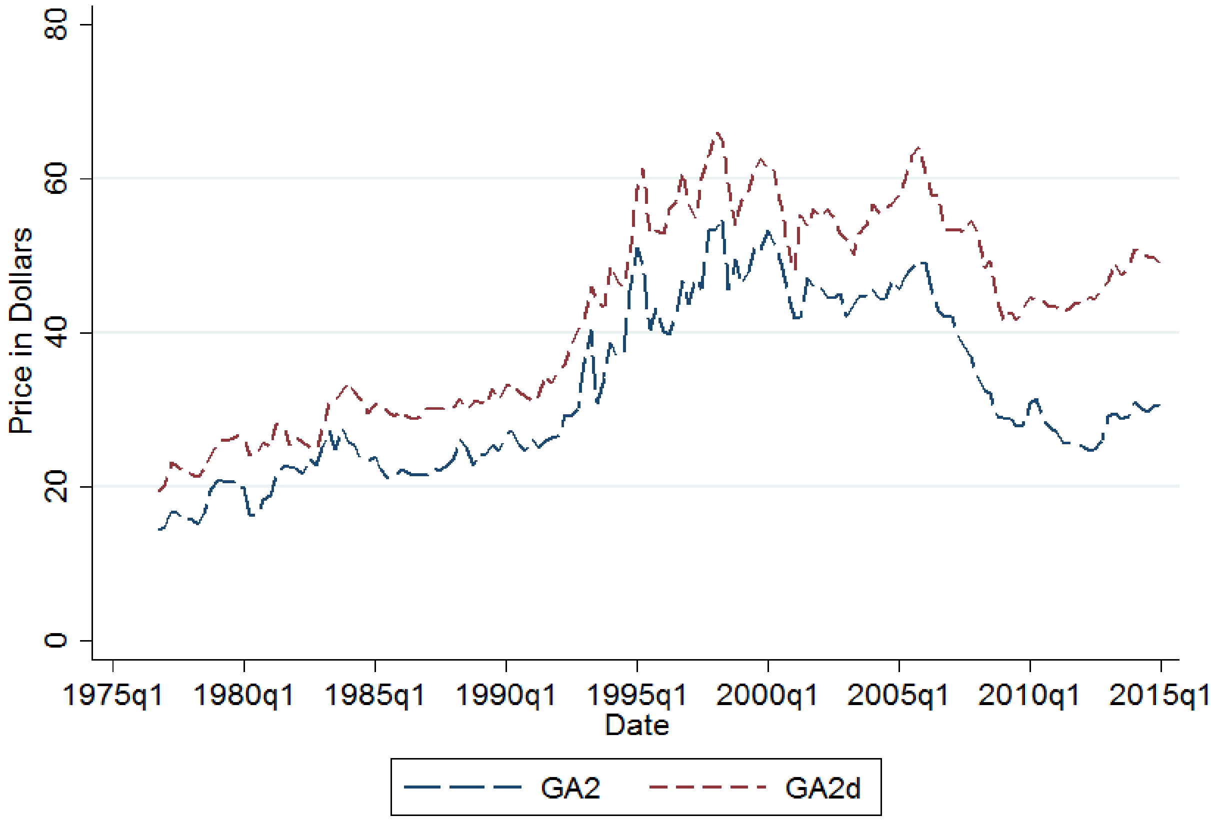

Figure 4.1: First-quarter stumpage and delivered prices for pine sawtimber for region 2 of Georgia by year. Stumpage price is blue, delivered price is red, and q1 = first quarter.

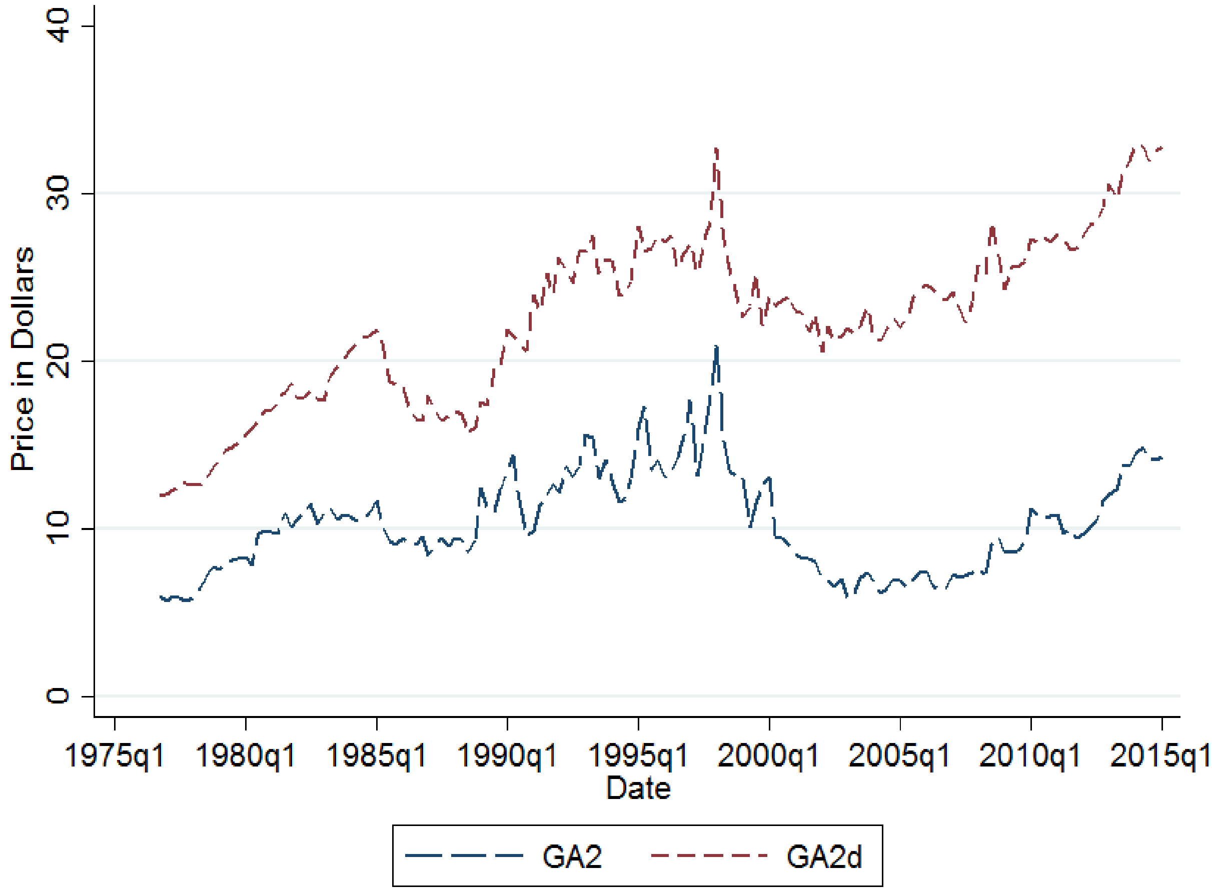

Figure 4.2: First-quarter stumpage and delivered prices for pine pulpwood for region 2 of Georgia by year. Stumpage price is blue, delivered price is red, and q1 = first quarter.

CHAPTER 5

CONCLUSIONS

This dissertation analyzes three different aspects of the timber market in the southeastern United States using Timber Mart-South data that are unique and robust from a region that is arguably the most decentralized developed forestry sector in the world. The southeastern U.S. timber market is made up of many relatively small independent landowners and many competing mills with no formal collective bargaining. Landowners decide whether to implement plantation style silviculture or any silviculture at all. Most interactions with smaller tracts of land are done as individual one-time contracts between small independent logging companies, which then have agreements with mills but are not restricted to a mill unless they so choose. Therefore, this data set provides a robust set of prices in perhaps the most freely developed market of its scale. It contains quarterly price data for 4 decades across 22 different regions. These are compiled using individual reports from voluntary participants in the transactions.

The market was examined across related, yet distinct, dimensions. The horizontal question of interconnected prices between regions is considered in Chapter 2, and which regions are actively competing as one integrated market was evaluated. Although previous studies have considered this question, endogenous structural breaks also were considered. If large market changes occur that affect the entire region simultaneously, an incorrect inference of cointegrated prices may be drawn. Markets may seem more interconnected then they are when an overwhelming change dominates true quarter-to-quarter changes.

Joint markets among regions were identified for pine sawtimber (PST) and pine pulpwood (PP) using the law of one price, which asserts that prices in one market converge to a single price after transportation and other transaction costs after a shock are considered. Mathematically this can be tested by determining if nonstationary prices converge. Single and double structural shocks that can account for a shift in level or in trend were introduced. These shocks are determined endogenously and coincide mostly with the growth of the southeastern timber market because of specific government restrictions in the Northwest and the housing crash of 2007, which sharply decreased the demand for lumber. This pattern was more apparent for PST than for PP. Some PP markets exhibited a second endogenous shock around the turn of the millennium rather than around 2007 because of the decline in demand for newsprint. The PST markets could be interpreted as nine minimarkets or six markets that were driven by three independent markets made up of the largest mill-capacity regions. The PP markets were one major market that spanned from northern Georgia to southern Texas (seven regions) and four markets made up of two regions. Compared to earlier studies, the markets were more fractured. The innovative outlier method (shift in trend) has less random cointegrated pairs than the additive outlier method (one period shift). One PST grouping paired low-capacity regions with high-capacity regions. The other grouping suggested that the highest production regions are each a unique singleton market. PP has a larger grouping that stretches from Texas to Georgia. The three regions with decreased production since 1990 were single markets.

Competition among vertical products (substitutes in the margins) is examined in Chapter 3. Chip-n-saw (CNS) is a product that has become widely recognized as a designation of wood between premium priced and large PST and cheaper and smaller PP; it can be an inferior substitute for PST while also being a higher priced alternative to PP. Landowners tend to let their trees grow larger while waiting for weak market prices to rise. Because mills would suffer significant costs from shutting down because of no input and given that prices are constantly changing, which product drives other prices is unclear.

The relationships among the three designated southeastern markets were determined using the Granger causality test. That test is based on the idea that price *a* cannot influence price *b* unless price *a* in previous periods has some explanatory power on current price *b*. The number of significant lags indicated by the Akiake information criterion varied between one and three for all markets. The Granger causality test using the method of Yamamoto–Toda indicated significant predictability of PST by CNS in regions 1 of Alabama and Georgia and regions 2 of Mississippi and North Carolina; PST by PP in region 1 of Alabama and regions 2 of Georgia and North Carolina; CNS by PST in both regions of Alabama and Georgia and region 1 of Florida; CNS by PP in regions 1 of South Carolina and Texas and regions 2 of Alabama and Georgia; and PP by PST in regions 1 of Alabama and South Carolina. Predictability of PP by CNS was not significant in any region. The Granger causality test using a differencing method indicated significant predictability of PST by CNS in regions 1 of Georgia and Mississippi; PST by PP in region 2 of Georgia; CNS by PST in both regions of Alabama and Georgia, region 1 of Mississippi, and regions 2 of Florida and South Carolina; CNS by PP in region 1 of Texas and region 2 of Georgia; and PP by PST in both regions of GA, region 1 of Alabama, and region 2 of South Carolina. Based on the number of significant predictabilities, the strongest causality was for prediction of CNS by PST, and the weakest was for prediction of PP by CNS. Of all the regions, the highest number of significant causalities was in region 1 of Alabama and region 2 of Georgia; no significant causalities were found in regions 1 of Arkansas and Louisiana. In general, rather than a consistent pattern, causality differed from region to region based on characteristics of each region. For example, region 2 of Georgia is mainly a PP producer and that drives the other two prices in the State. The abundance of each type of wood and the market power of the mills plays a part and changes pricing dynamics.

Logging margins, which were defined as the difference between stumpage (in the ground) and delivered (at the mill gate) pine prices, are examined in Chapter 4. Stumpage price is typically determined between the logger and the landowner, whereas delivered price is determined between the logger and the mill. Usually the loggers themselves take on the risk that this margin will cover their economic costs. Granger causality tests that either accounted for or ignored breaks and season were used. For PST, 32% of regions had significant delivered-to-stumpage causality, and 82% had stumpage-to-delivered causality regardless of whether or not breaks and season were considered. For PP, similar percentages were obtained if breaks and season were ignored, but the percentages decreased to 27% and 36%, respectively, if breaks and season were considered.

Effects of prices of significant inputs on stumpage and delivered prices were examined further for southern Georgia because it is a major producer of PST and PP. Mining/logging wages and midwestern housing starts were significant for stumpage and delivered prices. Industrial production and average hourly construction wage were significant for differences between stumpage and delivered prices. Industrial production was significant for delivered but not stumpage prices. In contrast, the 10-year treasury rate was significant for stumpage but not delivered prices. Delivered prices generally affected stumpage prices more; however, causality may be dependent on season and breaks. Without taking into account these factors, results may be incorrectly inferred. In general, various factors affect stumpage and delivered prices and their difference separately for PST and PP.

The examination of price effects for southern Georgia was limited by available data. Data were not consistent over the whole time period for labor, fuel prices, and machinery assumptions. Compounded with a limited number of data points, all effects could not be properly identified. For instance, an increase in the effect of hourly wage without considering the number of loggers working and the amount they harvest does not properly capture improved effectiveness of technology and capital. Therefore, the specifics of the coefficents are less important than the statistical significance of the results themselves.

In this dissertation, all regions in the southeastern United States were analyzed separately. Other studies also looked at the Southeast as one region, which increased the amount of data for analyses but also possibly ignored differences by State. A possibility for the analyses in Chapters 3 and 4 would be to use the regions defined in Chapter 2.

A significant limitation of the analyses in all three chapters was the lack of volume data. Elasticities and demand vs. supply shocks could not be evaluated quantitatively. In addition, the numbers of transactions and their distribution sizes were unknown. Large institutional investors may sell on a consistent basis as part of an investing strategy, whereas smaller landowners may be highly motivated by a good profit margin. In accounting for exogenous shocks (Chapter 2), information about flows of pine between regions and to ports would have been extremely useful. Determining relationships between CNS, PST, and PP (Chapter 3) would have benefited from knowing in which regions CNS designations were adopted earliest as well as how that designation may have fluctuated. Another possibility is that landowners who received a poor PST price might report it as CNS. The examination of stumpage and delivered prices (Chapter 4) would have greatly benefited from information on average size of landowner sales and the relative size and competition between mills. The density of sawtimber or pulpwood mills and the relative amount of silviculture investment could also help in understanding landowner business choices. Investment by a landowner suggests an interest in conducting intensive forestry regardless of product.

APPENDIX A: EXAMPLE OF COINTEGRATION ARRAY

Pine pulpwood price differenced augmented Dickey–Fuller cointegration test (values are augmented Engle–Granger statistics; number of lags determined by Akaike information criterion; symmetric across diagonal; computed with nominal prices; **P* < 5%, ***P* < 1%; critical values dependent on number of lagged terms and presence of a constant/trend)

Region	AL1	AL2	AR1	AR2	FL1	FL2	GA1	GA2	LA1	LA2	MS1	MS2	NC1	NC2	SC1	SC2	TN1	TX1	TX2	VA1	VA2
AL1		−2.34	−2.60	−2.86	−2.90	−1.67	−4.49**	−2.23	−4.70**	−6.89**	−1.72	−3.73*	−2.83	−2.05	−3.16*	−1.98	−4.05**	−3.95*	−4.84**	−1.70	−1.86
AL2	−2.34		−2.20	−2.90*	−3.12*	−2.35	−5.04**	−2.91	−3.72*	−5.48**	−0.59	−3.31	−2.84	−2.61	−3.48**	−5.31**	−3.70*	−4.18**	−5.33**	−2.28	−2.37
AR1	−2.60	−2.20		−5.20**	−1.99	−1.65	−2.72	−1.88	−2.68	−2.19	−1.64	−2.68	−2.71	−2.42	−2.63	−1.90	−3.84**	−.20*	−3.86**	−1.93	−1.77
AR2	−2.86	−2.90*	−5.20**		−2.39	−2.56	−2.71	−2.60	−3.67**	−2.51	−1.68	−2.77	−3.17*	−2.54	−2.79	−2.17	−3.85*	−3.83**	−3.48**	−2.15	−2.21
FL1	−2.90	−3.12*	−1.99	−2.39		−1.96	−2.70	−3.29	−2.83	−3.04	−1.24	−2.35	−2.07	−1.85	−2.03	−2.25	−2.32	−2.83	−3.35	−1.73	−1.78
FL2	−1.67	−2.35	−1.65	−2.56	−1.96		−2.58	−3.27	−1.88	−2.23	−0.39	−1.72	−1.78	−1.92	−2.09	−2.50	−2.40	−2.22	−3.91*	−1.78	−1.88
GA1	−4.49**	−5.04**	−2.72	−2.71	−2.70	−2.58		−1.77	−3.26	−3.61*	−1.37	−2.95	−2.92	−2.41	−2.81	−2.20	−3.24	−3.15	−3.87*	−1.92	−1.91
GA2	−2.23	−2.91	−1.88	−2.60	−3.29	−3.27	−1.77		−2.05	−2.75	−0.24	−2.12	−2.23	−2.31	−2.30	−3.14	−2.69	−2.12	−4.47**	−2.05	−2.17
LA1	−4.70**	−3.72*	−2.68	−3.67**	−2.83	−1.88	−3.26	−2.05		−5.34**	−2.00	−3.53**	−2.94*	−2.88*	−3.64*	−4.06**	−5.33**	−5.71**	−7.25**	−2.67	−2.36
LA2	−6.89**	−5.48**	−2.19	−2.51	−3.04	−2.23	−3.61*	−2.75	−5.34**		−2.04	−4.02**	−2.83	−2.79	−4.11**	−2.90	−4.23**	−3.19*	−4.79**	−2.37	−2.42
MS1	−1.72	−0.59	−1.64	−1.68	−1.24	−0.39	−1.37	−0.24	−2.00	−2.04		−1.22	−1.93	−1.23	−1.44	0.239	−3.05*	−2.81	−3.03*	−1.03	−1.20
MS2	−3.73*	−3.31	−2.68	−2.77	−2.35	−1.72	−2.95	−2.12	−3.53**	−4.02**	−1.22		−2.83	−2.86	−3.97**	−2.53	−4.64**	−3.83**	−4.23**	−2.40	−2.47
NC1	−2.83	−2.84	−2.71	−3.17*	−2.07	−1.78	−2.92	−2.23	−2.94*	−2.83	−1.93	−2.83		−1.97	−2.56	−1.76	−4.67**	−3.30*	−3.84**	−1.66	−1.65
NC2	−2.05	−2.61	−2.42	−2.54	−1.85	−1.92	−2.41	−2.31	−2.88*	−2.79	−1.23	−2.86	−1.97		−2.69	−–2.18	−4.09**	−3.24*	−3.70**	−2.24	−2.66
SC1	−3.16*	−3.48**	−2.63	−2.79	−2.03	−2.09	−2.81	−2.30	−3.64*	−4.11**	−1.44	−3.97**	−2.56	−2.69		−1.60	−4.67**	−3.66*	−5.24**	−2.20	−2.07
SC2	−1.98	−5.31**	−1.90	−2.17	−2.25	−2.50	−2.20	−3.14	−4.06**	−2.90	0.239	−2.53	−1.76	−2.18	−1.60		−3.23	−2.82	−4.74**	−2.08	−2.13
TN1	−4.05**	−3.70*	−3.84**	−3.85*	−2.32	−2.40	−3.24	−2.69	−5.33**	−4.23**	−3.05*	−4.64**	−4.67**	−4.09**	−4.67**	−3.23		−5.86**	−4.05**	−2.51	−2.27
TX1	−3.95*	−4.18**	−3.20*	−3.83**	−2.83	−2.22	−3.15	−2.12	−5.71**	−3.19*	−2.81	−3.83**	−3.30*	−3.24*	−3.66*	−2.82	−5.86**		−5.62**	−3.07*	−2.94
TX2	−4.84**	−5.33**	−3.86**	−3.48**	−3.35	−3.91*	−3.87*	−4.47**	−7.25**	−4.79**	−3.03*	−4.23**	−3.84**	−3.70**	−5.24**	−4.74**	−4.05**	−5.62**		−2.94	−3.15
VA1	−1.70	−2.28	−1.93	−2.15	−1.73	−1.78	−1.92	−2.05	−2.67	−2.37	−1.03	−2.40	−1.66	−2.24	−2.20	−2.08	−2.51	−3.07*	−2.94		−2.90*
VA2	−1.86	−2.37	−1.77	−2.21	−1.78	−1.88	−1.91	−2.17	−2.36	−2.42	−1.20	−2.47	−1.65	−2.66	−2.07	−2.13	−2.27	−2.94	−3.15	−2.90*	

APPENDIX B: FREQUENCY OF ENDOGENOUS STRUCTURAL BREAKS USING CLEMENTE, MONTAÑÉS, AND REYES PROCEDURE ON REGION PAIRINGS

Abbreviations: AO = additive outlier, IO = innovative outlier, PP = pine pulpwood, PST = pine sawtimber

	One break				Two breaks				
	PST		PP		PST		PP		
Year	IO	AO	IO	AO	IO	AO	IO	AO	Total
1978	0	0	0	0	0	0	0	0	0
1979	0	0	0	0	0	0	0	0	0
1980	0	0	0	6	0	0	0	0	6
1981	42	30	0	2	16	14	2	2	108
1982	24	8	2	0	27	22	4	4	91
1983	2	32	0	0	32	36	0	0	102
1984	0	8	0	0	7	12	0	0	27
1985	12	4	0	0	8	4	2	2	32
1986	14	6	0	0	2	2	2	2	28
1987	0	2	2	0	5	4	4	4	21
1988	4	4	2	2	16	24	18	36	106
1989	14	2	4	6	13	4	50	44	137
1990	6	2	2	0	3	2	12	10	37
1991	24	0	8	2	28	22	14	6	104
1992	30	8	8	16	70	64	34	26	256
1993	30	38	20	8	105	126	26	58	411
1994	30	28	26	16	32	34	48	66	280
1995	26	22	20	16	52	42	36	34	248
1996	12	28	18	14	54	64	48	32	270
1997	28	42	130	134	56	52	66	106	614
1998	18	4	50	24	35	36	62	62	291
1999	24	24	22	20	89	88	86	72	425
2000	2	0	10	4	13	12	36	16	93
2001	0	0	12	10	2	2	22	24	72
2002	4	2	6	6	16	14	16	10	74
2003	6	0	24	18	27	24	30	36	165
2004	12	24	10	12	42	40	48	34	222
2005	12	20	2	6	34	48	4	2	128
2006	48	28	12	2	98	84	26	20	318
2007	28	46	20	28	26	28	36	34	246
2008	2	10	2	8	8	8	30	42	110
2009	2	30	8	22	2	4	46	32	146
2010	6	4	0	2	4	6	30	22	74
2011	0	4	0	2	2	2	0	2	12
2012	0	2	0	28	0	0	2	0	32

APPENDIX C: ADDITIVE OUTLIER MARKET GROUPINGS

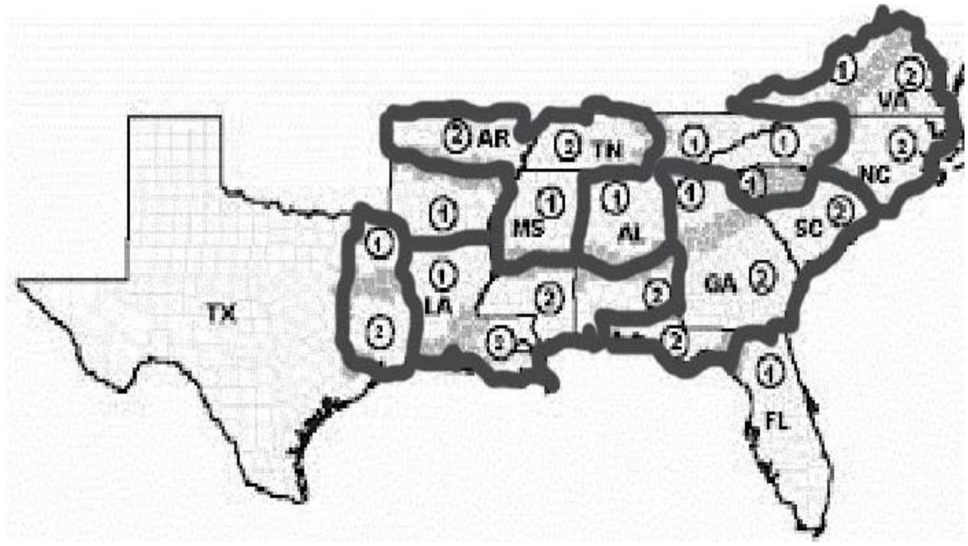

Figure C.1: Pine sawtimber Clemente, Montañés, and Reyes additive-outlier 2 breaks. Region is designated as two-letter State abbreviation and region 1 or 2.

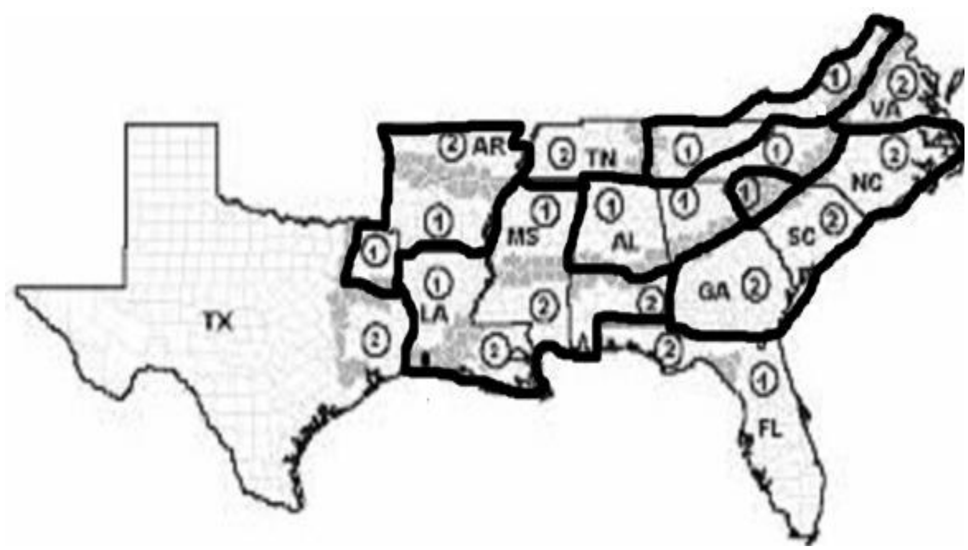

Figure C.2: Pine pulpwood Clemente, Montañés, and Reyes additive-outlier 2 breaks. Region is designated as two-letter State abbreviation and region 1 or 2.

APPENDIX D: BASELINE MARKET GROUPINGS WITH NO BREAKS

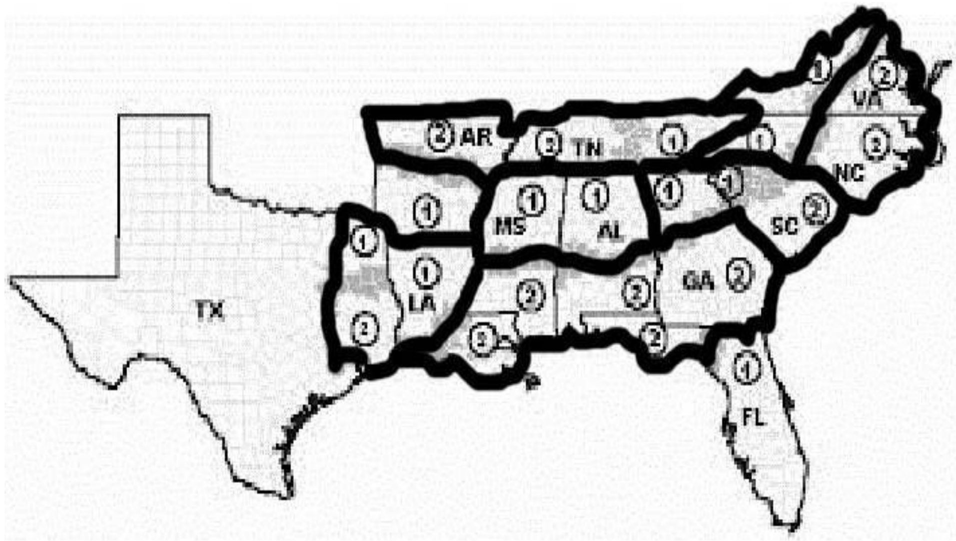

Figure D.1: Pine sawtimber augmented Dickey–Fuller pairwise test with lags determined by Akaike information criterion. Region is designated as two-letter State abbreviation and region 1 or 2.

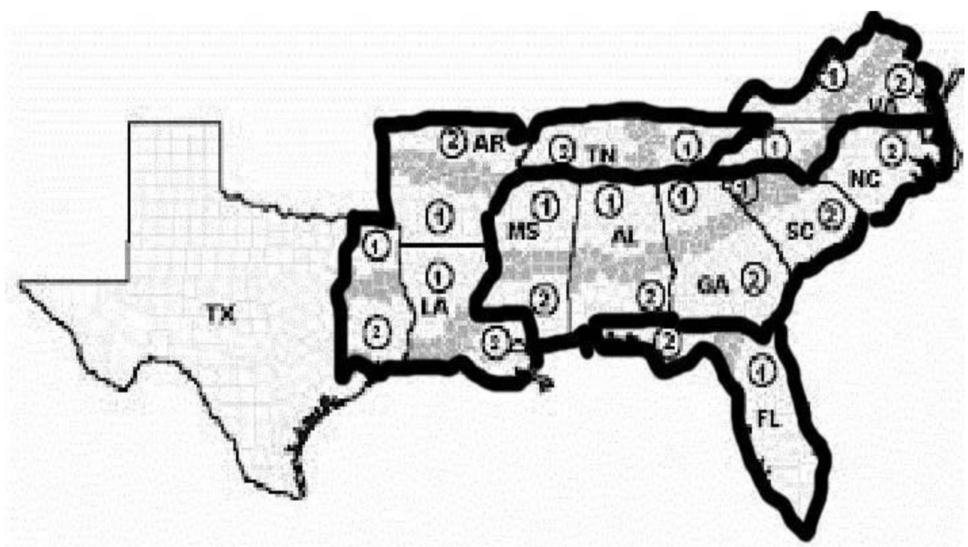

Figure D.2: Pine sawtimber augmented Dickey–Fuller pairwise test with lags determined by Schwartz information criterion. Region is designated as two-letter State abbreviation and region 1 or 2.

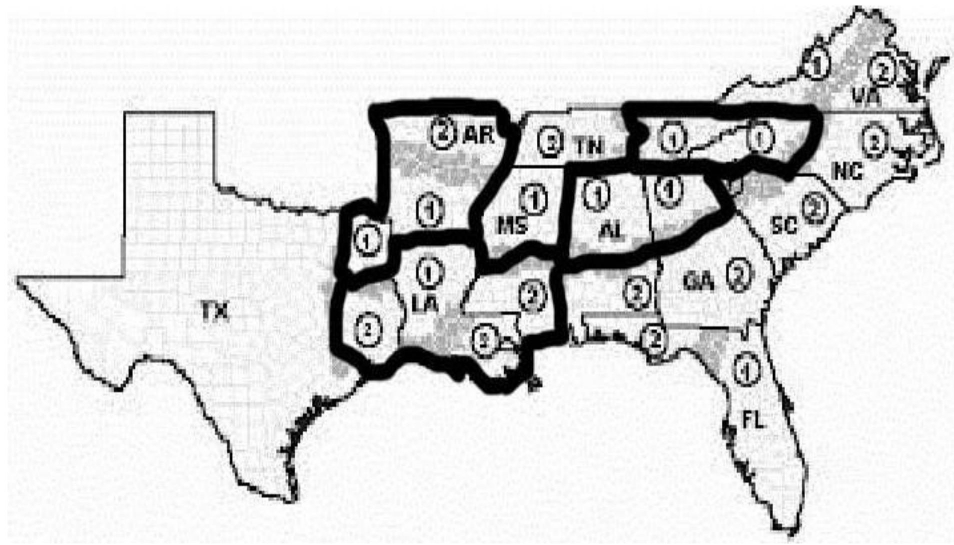

Figure D.3: Pine pulpwood augmented Dickey–Fuller pairwise test with lags determined by Akaike information criterion. Region is designated as two-letter State abbreviation and region 1 or 2.

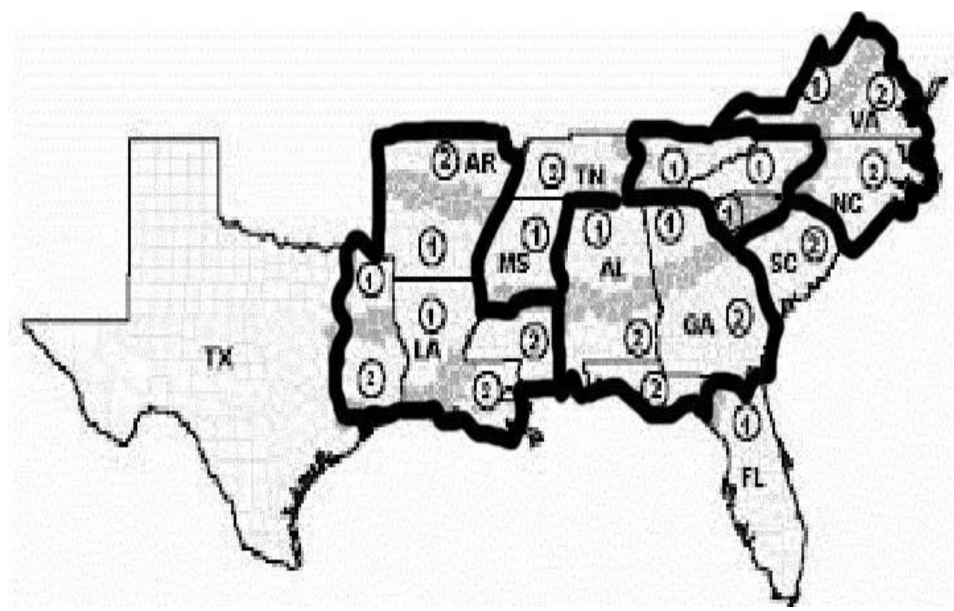

Figure D.4: Pine pulpwood augmented Dickey–Fuller pairwise test with lags determined by Schwartz information criterion. Region is designated as two-letter State abbreviation and region 1 or 2.