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Relation of pine chip-n-saw to sawtimber and pulpwood prices in the Southeastern United States: direction of influence.

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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 2016 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 four regions, PST by PP in three regions, CNS by PST in three regions, CNS by PP by three regions, and PP by PST by two regions. The Granger causality test using a differencing method indicated significant predictability for two fewer regions than the Yamamoto-Toda method, with eight regions in common. 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. 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. The results help better understand price relationships among timber stumpage products, the degree of substitutability among them, and the importance of individual market characteristics.

Keywords

chip-n-saw, cointegration, pine pulpwood, pine sawtimber, The Law of One Price, Timber Mart-South

Citation

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INTRODUCTION

Lumber production in the southeastern United States surpassed the North and the West in 1989 and remains the top region in terms of production (Howard and Jones 2019). 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 (~20-28 cm) in diameter at breast height) is a relatively new designation for timber product that lies between the more traditional designations of pulpwood (~6+inches (~+15 cm) in diameter at breast height) and sawtimber (~12 inches (~30 cm) 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 in 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 behavior across the region. Several previous studies used TMS data to measure the relationship 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 Southeast was more cointegrated than 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 in 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 non-competitive. Because there was no long-term relationship between pulpwood and pulp products, Zhou and Buongiorno (2005) suggested that paper mills behave like monopsonists.

Research has also 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.

The addition of CNS to studies on the interrelationship sawtimber and pulpwood is fairly recent development. Parajuli et al. (2016) examined sawtimber, CNS, and pulpwood in four states and found pulpwood and CNS have unidirectional effect on sawtimber in Arkansas and Texas and found no evidence of bidirectional effects. Tanger and Parajuli (2018) applied a supply and demand model in Louisiana and cross-price elasticities suggesting some degree of substitutability between CNS and sawtimber. Parajuli et al. (2019) looked at the dynamics of CNS relative to sawtimber and pulpwood using the Subregional Timber Supply Model. They found the relationships between the products changing over time, variation across markets, and projected increased CNS prices in the future.

The purpose of this study was to extend the research of previous studies to more markets and more time periods with an 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 and Mirza 1999).

METHODS

Cointegration analysis allows testing whether markets follow the law of one price (LOP) and behave as one market (Uri and Boyd 1990). Stationarity in the analysis can be determined using the augmented Dickey–Fuller (ADF) test (Dickey and 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 and 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.

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 Yamamoto (1995) and Dolado and Lütkepohl (1996), here called TYDL. The TYDL VAR model is expressed as Equation 1:

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

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

(1)

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 and Williams 2000). The standard VAR model is identical except that the *B* matrix is omitted. The VAR model may be misspecified with integrated of order 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 Equation 2:

$$w = (Rb - r)^{\prime}\, RVR^{\prime}\, (Rb - r)^{\prime}\,,$$

(2)

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 and 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 Misztal et al. (2024).

Lag length is critical for correctly inferring Granger causality (Thornton and 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 expressed in Equation 3:

$$\mathrm{LM} = (T - d - 0.5)\ln\frac{|\hat{\Sigma}|}{|\tilde{\Sigma}|} \tag{3}$$

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 the second quarter (2Q) of 1980 through the first quarter (1Q) 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 and Pye 2000). Each region will be identified by its two-digit state code followed by 1 or 2 denoting region number. The 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 and Dorfman 2015). More data points are available for stumpage than delivered prices, and stumpage prices are more relevant to TMS and their subscribers. The 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 1.

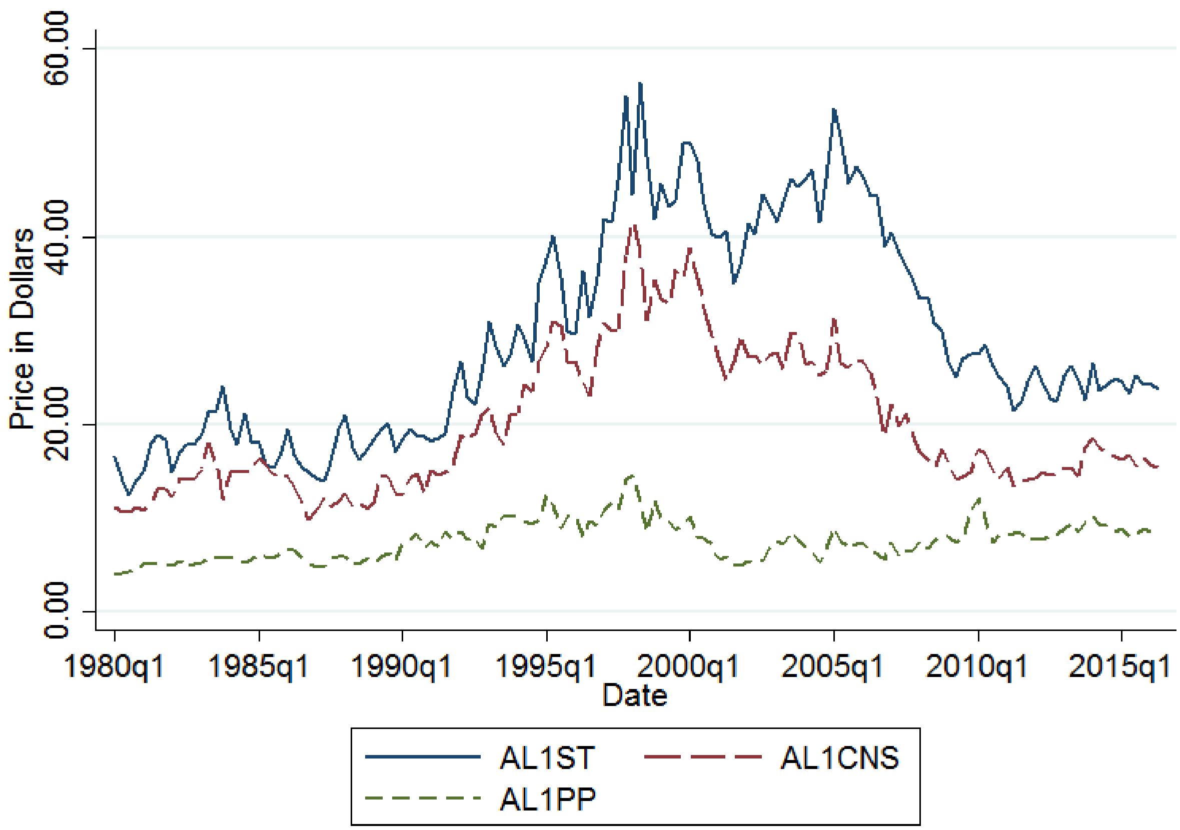

Figure 1. First-quarter prices of pine sawtimber, chip-n-saw, and pine pulpwood in region 1 of Alabama by year. q1 = first quarter, ST = pine sawtimber, CNS = chip-n-saw, and PP = pine pulpwood.

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 price changes 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 research.

TMS data used in this research are expressed in the United States customary units of measurement. The inch equals 2.54 cm. Standing timber (stumpage) prices are expressed in U.S. dollars per ton (short ton equal to 907.2 kg).

RESULTS

Table 1 shows the number of lags as indicated by several criteria and as used in subsequent analyses.

Table 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.*

The AIC tests indicate the highest lags, up to 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 and 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 2.

Table 2. Probabilities[1] of Granger causality for product prediction[2] using the Yamamoto–Toda method with augmented vector autoregression as defined by Toda and Yamamoto 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.

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. The contents of Table 2 are visualized in Figure 2.

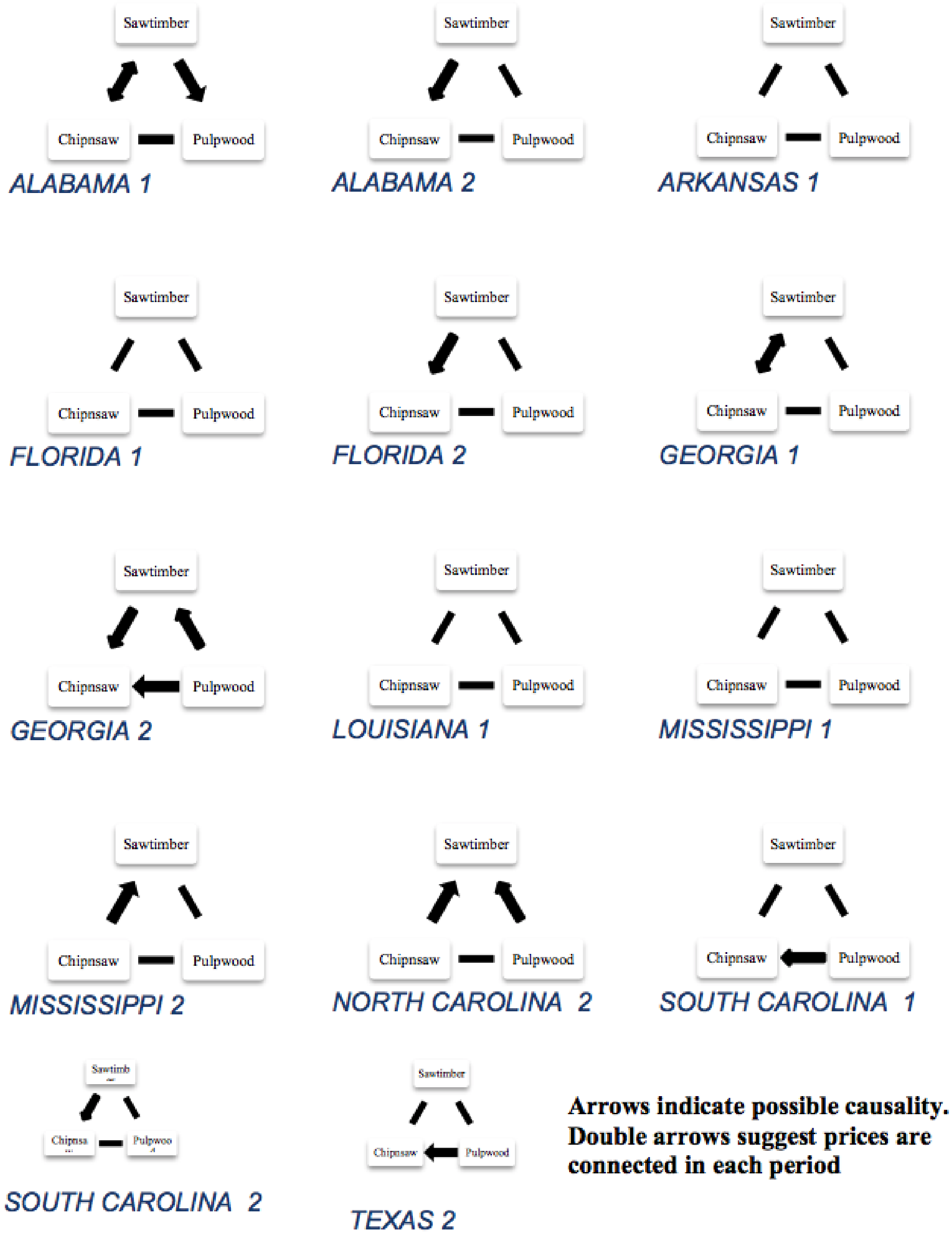

Figure 2. Causality at the 5% level using the Yamamoto–Toda method with augmented vector autoregression as defined by Toda and Yamamoto and by Dolado and Lütkepohl.Only GA2 shows causality across the three directions. Only AL1 and NC2 show causality in two directions, with a single direction for AL2, 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 shows the same probabilities as in Table 2 in a model without the TYDL correction.

Table 3. Probabilities[1] of Granger causality for product prediction[2] using the Yamamoto–Toda method without augmented vector autoregression as defined by Toda and Yamamoto 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.

The results are visualized in Figure 3 with corrections for pretesting bias.

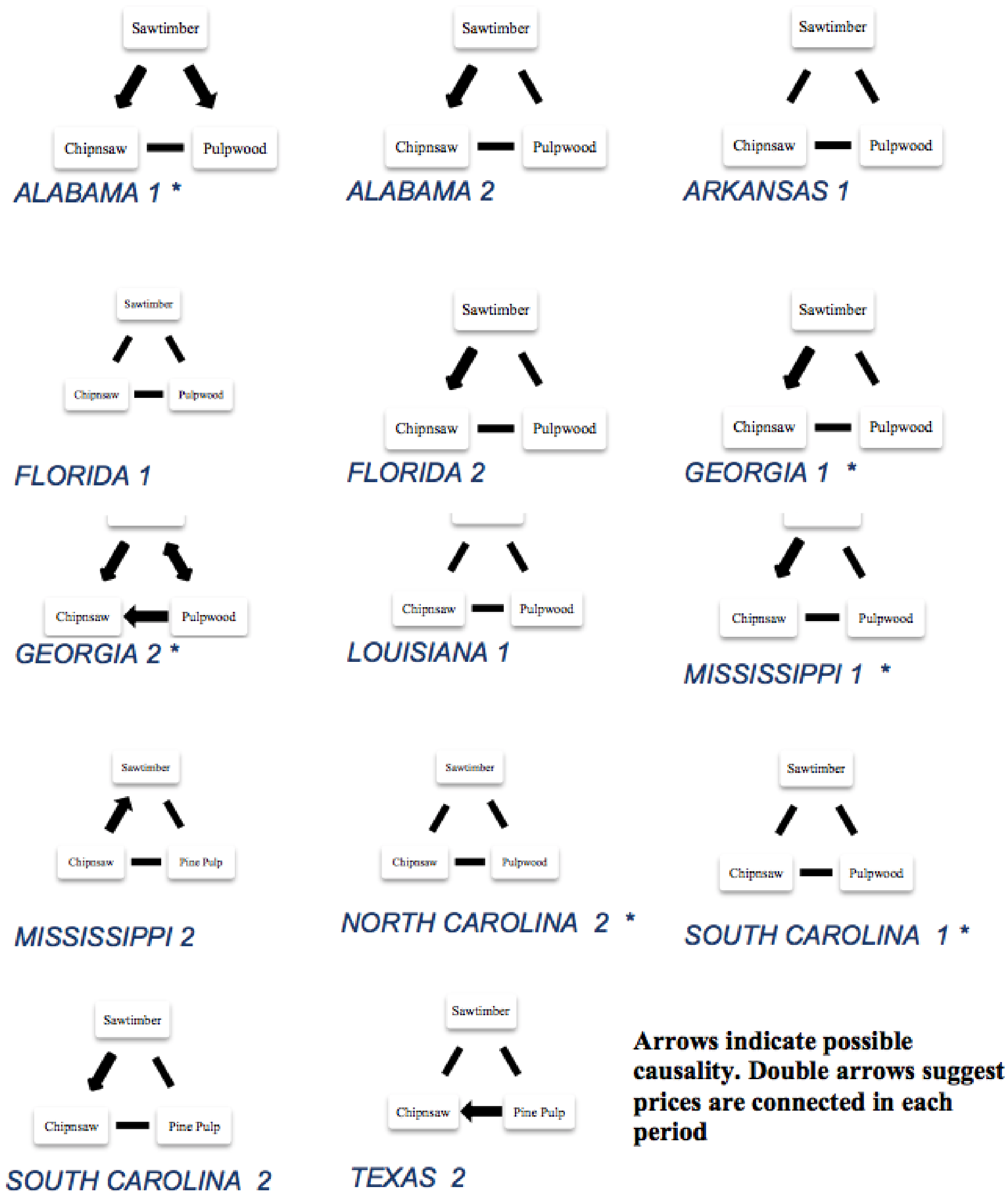

*Figure 3. Causality at the 5% level using the Yamamoto-Toda method without augmented vector autoregression as defined by Toda and Yamamoto and by Dolado and Lütkepohl; * indicates differences between models with and without augmented vector autoregression.*

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 and Yamamoto 1995). It is used because it is not dependent on the level of integration or cointegration.

Table 4 shows the results of the JH cointegration tests for each State.

Table 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.*

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 integrated of order 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. Our previous study (Misztal et al. 2024) 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 pairings 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 research can be compared with those of Parajuli et al. (2016) 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 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 research 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 (timber product definitions) in the southeastern United States. It is one of the few forested regions in the world with no legal conventions when it comes to evaluating stumpage and defining timber products. 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.

The understating of price relationships among timber products has implications for forest owners and managers in deciding how to manage their forests in regard to product mix and rotation length.

Depending on market conditions, some landowners may, for example, decide to shorten rotations and focus on PP and CNS products. This, in turn, will have implications for financial returns. For wood buyers, the degree of substitutability between stumpage products and their price interactions are important variables, particularly during times of market turmoil and may help in developing more effective wood procurement strategies in terms of wood cost and availability.

MS2 has had a relatively large timber inventory with a high site index suitable for high-value products such as poles and veneer-quality logs. 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 drawings on 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 a 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 suffers 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. 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.

CONFLICTS OF INTEREST

The authors confirm there are no conflicts of interest.

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