

Causes and Relationships between Pine Delivered and Stumpage Prices in the Southern U.S.

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How to cite this paper: Misztal, M. D., Siry, J. P., Mei, B., Harris Jr., T. G., & Bowker, J. M. (2026). Causes and Relationships between Pine Delivered and Stumpage Prices in the Southern U.S. *Open Journal of Forestry*, 16, 20-33.
<https://doi.org/10.4236/ojf.2026.161002>

Received: September 5, 2025

Accepted: November 25, 2025

Published: November 28, 2025

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Abstract

Data included quarterly stumpage and delivered pine prices across 11 states in the U.S. South. Data from all states were available in two regions. The first analysis used Granger causality to determine whether stumpage prices were determined by delivered prices or the opposite. Granger causality tests accounted (ACC) for or ignored (IGN) breaks and seasons. For sawtimber, with either ACC or IGN, 32% of regions had significant delivered-to-stumpage price causality, and 82% of regions had stumpage-to-delivered price causality. For pulpwood, similar percentages were obtained with IGN, but with ACC, the percentages changed to 27% and 36%, respectively. Effects of several factors on stumpage and delivered prices, and their differences, were determined for the largest region, Georgia 2. None of the factors was significant for all prices. Mining/logging wages and housing starts in the Midwest were significant for stumpage and delivered prices. Industrial production and average hourly wage construction were significant for the differences. Industrial production was significant for delivered but not stumpage prices. Conversely, the 10-year treasury rate was significant for stumpage but not for delivered prices. Delivered prices generally affect more stumpage prices, although the causality may be season and break dependent. In general, various factors affect stumpage and delivered prices and their difference, separately for sawtimber and pulpwood.

Keywords

Timber Markets, Timber Prices, Granger Causality, Cointegration

1. Introduction

Stumpage prices are the prices paid to the landowner to harvest marketable trees on a given parcel of land. Delivered prices are the prices paid to the logger at the gate of the mill. The difference between the two is all the costs incurred in between. These include logging, skidding, hauling, and the opportunity cost of capital, insurance, and any other costs associated with getting the appropriate product to the appropriate mill.

Typically, a mill will pay the same amount for two identical hauls of wood. Stumpage prices, on the other hand, vary greatly. One reason for variation is the characteristics of the land, such as incline, distance to the road, and distance from the mill. Moreover, the logger has to manage the changing costs of their inputs, such as labor, maintenance of machinery, fuel, and others.

A mill has much greater bargaining power than a landowner. It is costly for a logger to send a haul to a different mill, and the price of stumpage has already been paid. However, loggers have many more landowners with whom they can bargain. They will also be willing to go after harder-to-get stumpage if the mill increases delivered payments. Long-term relationships between mills and loggers are increasingly important. The mills may be liable if the shipments they receive are illegally cut or if taxes are not paid.

The Timber Mart-South (TMS) reports quarterly timber product prices from 11 states in the southern U.S. starting from 1976. The long time period also contains distinct structural breaks in the market that significantly affected market behavior across the region. Several previous studies used this data to measure the relationships in timber prices across regions. [Yin, Newman, & Siry \(2002\)](#) examined the pine pulpwood and pine sawtimber prices using appropriately specified pairwise Dickey-Fuller tests to test for cointegration. Grouped regions were further verified with Johansen tests. They rejected the presence of the law of one price (LOP) throughout the entire region but found evidence of subregions that function as unified markets. While their market definitions were restricted to geographically cohesive groups, they did find evidence of cointegration between geographically noncontiguous regions. [Bingham et al. \(2003\)](#) considered outside policy factors, such as the reduction of timber harvesting on federal land in 1988. Their results suggested that price shocks were more quickly disseminated along regions with a coastline, creating one large market. There was also evidence of two separate interior markets in the northern and western parts of the southern region, although these were not defined explicitly. [Zhou & Buongiorno \(2005\)](#) created a space-time autoregressive moving average model to which they applied impulse shocks. Price shocks did not seem to be either statistically or 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, which overlapped with all the other submarkets. [Hood & Dorfman \(2015\)](#) analyzed the dynamics of the TMS stumpage regions using 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 due to the housing boom. Markets tended to segment more as the market worsened.

Besides spatial price relationships, there are other price relationships that would be of interest to forest owners and anyone trying to understand the market dynamics of the industry. [Ning & Sun \(2014\)](#) looked at vertical prices by examining three prices along the demand chain in the southern and western U.S. between 1977 and 2011. They used linear and threshold cointegration to model the relationship between softwood stumpage and delivered prices, and then delivered prices and lumber prices. The U.S. South is more cointegrated than the West, and the first stage is more closely related than the second stage. Prices are more responsive with larger margins than with smaller ones. [Nagubadi, Munn, & Tahai \(2001\)](#) examined hardwood pulpwood, mixed hardwood sawtimber, and oak sawtimber in six southern states. They found little evidence of market integration across regions and found the least integration among pulpwood. [Zhou & Buongiorno \(2005\)](#) considered causality tests among southeastern pine sawtimber and pulpwood prices in relation to forest product prices for the U.S., including softwood lumber, paper, and wood pulp. They found no cointegration between any of the prices, and they found evidence that national lumber prices Granger-cause southern sawtimber prices. The lack of any causality in the pulpwood markets suggested the southern pulp markets did not compete amongst each other. Because there was no long-term relationship between pulpwood and pulp products, the authors suggested that paper mills behaved like monopolists.

There has also been research into the nature of prices and harvesting decisions. [Mei, Clutter, & Harris \(2010\)](#) tested the forecast capability of various time series models on pine sawtimber stumpage prices in 12 southern timber regions in the United States. [Prestemon & Wear \(1999\)](#) analyzed aggregated North Carolina stand-level data to measure the price responsiveness over time as the vintages of inventory shifted using a probit model. Among their results were that higher sawtimber prices led to lower pulpwood production, higher pulpwood prices led to higher pulpwood production, and that harvest timing was insensitive to price changes.

[Parajuli & Chang \(2015\)](#) analyzed the dynamics of pine sawtimber (PST), pine pulpwood (PP), and chip-n-saw (CNS) prices in the Southcentral U.S. They found that both PP and CNS prices were major covariates of the PST price. They also found that no bi-directional causality existed between any pair of forest product prices. They reasoned that harvesting PP and CNS were short-term decisions that would influence the more long-term decision-making processes for sawtimber. They suggested that landowners use them to predict PST prices.

The purpose of this study is to extend the work to more markets with additional focus on methodology. The time period and geographical area are both broadened. Our methods eliminate possible bias associated with pretesting for cointegration and stationarity. This paper analyzes the relationship between PP and PST

timber products in each state using cointegration (Johansen, 1995) and Granger causality (Granger, 1969). The former implies a long-term connection, while the latter suggests a quicker short-term association. This interpretation is standard, but may be oversimplified, as a long-term relationship may not always indicate a short-term relationship (Fugarolas, Mañalich, & Matesanz, 2007). To test for Granger causality, we derive a standard vector autoregression (VAR) model and an augmented specification that eliminates pretest bias and leads to more robust results (Giles & Mirza, 1999).

2. Methods

Cointegration analysis allows us to evaluate whether markets follow the LOP and behave as one market (Uri & Boyd, 1990). Given an exogenous price shock, such as a natural disaster that changes the distribution of the age structure of timber, the shock should converge back to a single price in the long run. Most prices exhibit non-stationary behavior over time. If their first differences are stationary, they must be of order I (1) (Takayama & Judge, 1964). If a combination of two prices can be expressed as a time series that is stationary (order I (0)), the two are said to be cointegrated. This implies that changes in price among two separate products are perfectly transmitted over time, adjusting for exogenous factors such as differences in transaction costs.

The Augmented Dickey-Fuller test (ADF) is the standard for determining stationarity (Dickey & Fuller, 1979). The model can be represented as a random walk with drift $y_t = \alpha + y_{t-1} + u_t$, where α is the constant drift term, y_{t-1} represents the observed value of the previous period, and u_t is an independent and identically distributed error term. By including a time trend and differencing, we can fit the standard Dickey-Fuller model to be tested $\Delta y_t = \alpha + \rho y_{t-1} + \delta_t + u_t$ with ordinary least squares (OLS). The null hypothesis suggests $\rho = 0$, indicating the time series is non-stationary 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, while the latter implies a deterministic trend. ADF improves the standard model by addressing serial correlation by including lag terms of the differenced time series. This paper uses the ADF with both α and δ , as well as an ADF that includes a trend only if it is statistically significant for an individual price series. Because the prices never start at zero, the possibility of the intercept being non-significant 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. Akaike Information Criterion (Akaike, 1973) is represented as $AIC = 2k - 2\ln(L)$, where k is the number of estimated parameters and L is the maximum of the likelihood function. Schwartz Criterion (Schwarz, 1978) is represented as $BIC = -2\ln(L) + k\ln(n)$ where n is the number of observations,

k is the number of free parameters, and L is the likelihood function. The Hannan–Quinn information criterion is represented as $HQIC = -2L + 2k \ln(\ln(n))$ where n is the total number of observations, k is the number of free parameters, and L is the likelihood function.

The Johansen method (JH) (Johansen, 1995) tests for cointegration over bivariate and multivariate series. 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 $I(1)$ variables (in our case, $K = 2$), Π is the $(K \times 1)$ long-run coefficient matrix, Γ are the $(K \times K)$ coefficient matrices for every lagged variable, and ε_t is a $(K \times 1)$ vector of normally distributed errors that are serially uncorrelated. Γ is estimated using maximum likelihood. The rank of $\Pi(r)$ 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 is stationary, while $r = 0$ implies there are no linear combinations that are $I(0)$. With $n I(1)$ series, full cointegration would imply rank $r = n - 1$.

Granger causality 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 does not help predict X_t , then z_t cannot be said to cause X_t . We ignore the possibility of consumers' expectations of future prices affecting prices today. Modeling expectations requires significantly stronger assumptions and complexity.

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

$$w = (Rb - r)' (RVR')^{-1} (Rb - r)$$

where Rb 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. $m = 1$ since the maximum order of the endogenous variables is 1. The null hypothesis

$H_0 : A_{kl,1} = A_{kl,2} = \dots = A_{kl,p} = 0$, where k and l are one of PST or PP, implies that variable l does not cause variable k . The causality tests are conducted using both the standard VAR and Toda & Yamamoto (1995) and Dolado & Lütkepohl (1996) (TYDL) modified VAR.

Exogenous variables such as seasonal dummy variables are added without having to change the estimation procedure (Park & Phillips, 1989; Sims, Stock, & Watson, 1990). Bauer & 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 & Batten, 1985). Choosing arbitrary lag lengths leads to contradictory results. The significant number of lags (b) 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 is run. We use the Lagrange Multiplier (LM) test for autocorrelation among residuals in VARs (Johansen, 1995). The LM for any given lag is

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

where T is the number of observations and $\hat{\Sigma}$ is the maximum likelihood 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 & 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 non-normality, kurtosis, and skewness of disturbances, but this is not an issue for Granger causality testing in VAR models (Johansen, 2004). 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 & 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. We use a degrees of freedom correction for small samples, which changes the maximum likelihood divisor of $1/T$ to $1/(T - m)$, where m is the average number of parameters in each equation.

While causality analyses provide statistical indications of the direction of causality, they do not indicate which factors influence that causality. Those factors can be determined by direct regression on prices. We consider factors of production that influence the price of stumpage, the delivered price, and the margin between pine sawtimber and pulpwood. 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 proxies for these

costs to establish the significance of each cost with respect to logging margins as well as delivered and stumpage prices separately. We regress each 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.

3. Data

TMS collects data that discounts specific loads from premiums paid for long distances or difficult conditions. The mill price is supposed to be the standard price for local timber, and additional premiums due to haul distance, for example, are not included in the price reported. Stumpage prices may be biased downward mainly due to premiums for large harvest areas and the permission to clear-cut. The mill typically has a contract with each logger for a specified price per product and will manipulate to discourage products they do not 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 monopolistic, with one firm buying every type of wood in its vicinity, to a more diversified buying market. Now, different types of timber products from the same logger may go to different companies, not just different mills.

We analyze TMS stumpage and delivered wood prices of 11 states. Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia each contain data from their inception in the fourth quarter (4Q) of 1976 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 & Pye, 2000). In this paper, each region will be identified by its two-digit state code, followed by 1 or 2 denoting the region number. We focus 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. Misztal et al. (2024) provide a detailed description of the data.

We focus on nominal level prices as suggested by (Bingham et al., 2003; Prestemon, 2003). Real price data are also analyzed and result 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. In most cases, prices tended to diverge in 2008, which may imply greater market power of the mills in relation to the loggers. Many states also exhibited price spikes towards the end of the 1990s for both stumpage and delivered timber. The logarithms of prices are also used when the data exhibit great variability, which is not the case in this data. Cointegration tests on natural logarithms of prices imply a stronger interest in the 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, 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 the average hourly wage for production and for construction. Production serves as a control for unsupervised wages, while 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) of agricultural machinery is used to account for inflation, as well as a proxy for buying capital machinery. Industrial production works similarly. We use the 10-year interest rate to represent the cost of borrowing. Finally, diesel 2 is used to account for the changing cost of fuel. In evaluating the effect of these factors on stumpage and delivered prices and their differences, we relied on GA2 timber price data. The GA2 region is characterized by very well-developed timber markets and wood processing industries, including a large number of pulp and paper mills and sawmills, and has robust stumpage and delivered price data.

4. Results

Table 1 presents Granger causality for PST, either ignoring (IGN) or accounting (ACC) for breaks and seasons. Out of 22 regions, IGN causality indicated that 19 regions had significant causality of stumpage causing delivered prices, while the reverse causality was significant in only 7 regions. ACC 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.

Table 1. Pine sawtimber Granger causality.

	Basic				Control			
	Lag	Rank	Delivered Causes Stumpage	Stumpage Causes Delivered	Lag	Rank	Delivered Causes Stumpage	Stumpage Causes Delivered
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	0.5	0**	2	1	0.14	0.00**
GA2	3	0	0.04*	0**	2	0	0.03*	0.00**

Continued

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	0.1	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**	00.00**
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**

Note: Basic is a VAR without dummy variables for breaks and seasons. Control controls for breaks and seasons. Stumpage refers to stumpage, and delivered refers to delivered prices. *Indicates 5% significance. **Indicates 1% significance.

Table 2 presents similar analyses for PP. The results of basic causalities are almost the reverse of those for PST, where only 8 regions had a significant causality of stumpage prices causing delivered prices, while the reverse causality was significant in 17 regions. Control causality was quite different, with 6 regions showing a significant causality of stumpage causing delivered prices, while the reverse causality was significant in only 9 regions, respectively. 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 delivered prices. Both regions of Texas and NC1 show a long-term cointegrating relationship, although they are also relatively small markets. Delivered prices tend to impact future stumpage prices, specifically in AR1, FL2, LA1, NC1, TX1, and TX2.

Table 2. Pine pulpwood Granger causality.

	Basic		Delivered Causes Stumpage		Control		Delivered Causes Stumpage	
	Lag	Rank	Delivered Causes Stumpage	Stumpage Causes Delivered	Lag	Rank	Delivered Causes Stumpage	Stumpage Causes Delivered
AL1	2	0	0.04*	0.39	2	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*

Continued

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**

Notes: Basic is a VAR without dummy variables for breaks and seasons. Control controls for breaks and seasons. Stumpage refers to stumpage, and delivered refers to delivered prices. *Indicates 5% significance. **Indicates 1% significance.

Table 3 shows the significance of several factors on stumpage and delivered prices, and their difference for both PST and PP in the GA2 TMS region. When considering the logging margins for sawtimber, the PPI of agricultural machinery, the 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, as were diesel and housing in the Northeast, all well beyond the 1% level. Sawtimber shows both stumpage and delivered prices are significant at the 1% level for all wages, fuel, and southern housing starts, and 5% significance for midwestern housing starts. Pulpwood had significance in logging wages, northeastern and midwestern housing starts, and agricultural machinery. Stumpage was also significant for unskilled labor and fuel, while delivered prices were significant for skilled labor and industrial parts.

Table 3. Significance of factors of production for pine sawtimber and pulpwood.

	$P > Z $ Pine Sawtimber			$P > Z $ Pine Pulpwood		
	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
Housing Starts West	0.11	0.14	0.47	0.60	0.37	0.19

Continued

Housing Starts Northeast	0.39	0.09	0.19	0.00**	0.00**	0.00**
Housing Starts Midwest	0.42	0.02*	0.03*	0.09	0.00**	0.00**
Agricultural Machinery PPI	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
Average Hourly Wage 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**

Notes: *Indicates 5% significance. **Indicates 1% significance.

5. Discussion and Conclusion

Stumpage tends to drive the PP delivered price. With PST, there is less impact compared to PP. There are two theories that would explain these interactions, which cannot be proven or disproven using our current data and methodology. One is pricing information, as suggested in [Parajuli & Chang \(2015\)](#). Given the higher value of sawtimber and its increased relative volatility, landowners are not willing to wait for 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. The second is bargaining power. With sawtimber as a premium product, the landowners 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, pulpwood sellers may be price takers.

Logging margins can be said to serve as a proxy for determinants of the logging companies. Both sawtimber and pulpwood had stand-ins for the cost of machinery and its repair, wages, and interest rates as significant factors, which would be expected and are consistent with previous studies. Pulpwood was also sensitive to skilled wages, diesel, and housing starts in the Northeastern U.S. The latter is probably accidental, but diesel and skilled labor may suggest that increases in transportation and management costs are especially significant for low-margin products. It is also possible that there is more bargaining power for sawtimber, and loggers are able to pass on these two costs to the mills. Local housing starts also suggest that sawtimber served mostly southern markets. Pulpwood served mostly midwestern and northeastern markets, suggesting it may have been easier to transport the pulpwood and consume it near those industrial centers in 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 are taken by the landowners. Fuel and unskilled 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 for the buyers and sellers. 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 evidence that loggers have become more diverse in their mill deliveries. At one time, one company would buy all grades of timber from the surrounding area, but this trend is waning.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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