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Impacts of COVID-19 on the US manufactured wood industry: evidence from softwood lumber and structural panels

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ABSTRACT

The COVID-19 pandemic introduced unprecedented volatility into the US manufactured wood products market, with the price of softwood lumber nearly quadrupling within a year, reaching its highest level since 1995. This paper examines the substantial price fluctuations in major wood products, focusing on Spruce-Pine-Fir and Southern Yellow Pine softwood lumber, as well as Oriented Strand Board sheathing. Using vector autoregressive and vector error correction models, this study investigates the relationships between wood product prices and various macroeconomic factors. The analysis reveals that labor market disruptions and shocks in the housing

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sector were significant contributors to the observed price volatility during the pandemic.

Keywords Softwood lumber, Wood panels,
Vector error correction model (VECM), COVID-19 pandemic

Paper type Research paper

1. Introduction

The COVID-19 pandemic, caused by the SARS-CoV-2 virus, had a profound impact on the global economy. The virus is highly transmissible through airborne particles; therefore, the most effective way to mitigate its spread is to limit social interactions (CDC, 2020). In March 2020, the World Health Organization (WHO) officially declared COVID-19 a global pandemic, followed by a national emergency declaration in the USA (WHO, 2020). In response, many states implemented “shelter in place” protocols, urging residents to stay indoors and prohibiting group gatherings. This led to widespread disruptions across multiple sectors, including construction and related manufacturing industries. Numerous ongoing projects were halted, putting significant pressure on production capabilities and supply chains, further complicating the economic challenges induced by the pandemic.

Commodity prices in the forest product industry have exhibited significant volatility since the beginning of the pandemic. The price of Spruce-Pine-Fir (SPF) softwood lumber increased from $326 per thousand board-feet (mbf) in April 2020 to $1,610/mbf in May 2021, the highest level recorded since 1995, before falling back to $350/mbf by the end of August 2021. A subsequent price surge occurred in March 2022, with SPF lumber reaching $1,250/mbf, followed by a decline to $348/mbf in May 2023, effectively returning to pre-pandemic levels. Similar dynamics were observed in the market for wood-based panels, particularly Oriented Strand Board (OSB). These significant fluctuations in lumber and panel prices imposed higher input costs on the construction and home renovation sectors, also introducing considerable uncertainty into production planning and resource allocation decisions among firms operating in construction, woodworking, and forest-related industries.

The wood product manufacturing sector represents an important part of the US economy, serving as a major source of employment within the broader manufacturing industry. According to the National Industry-Specific Occupational Employment and Wage Estimates published by the U.S. Bureau of Labor Statistics (BLS) (BLS OEWS, 2022), the wood product manufacturing sector employed about 424,000 individuals and had an annual payroll of approximately $19.2bn in 2022, making this sector a fundamental economic driver. In addition to being the world's leading producer of wood products, the USA is also a leading consumer. In 2017, total US lumber consumption was estimated at 54.7 billion board feet, with domestic production accounting for 42.2 billion board feet, while the remainder was sourced from imports, primarily from Canada (Howard and Liang, 2019). By 2022, approximately 80% of U.S. softwood lumber imports originated from Canada, with additional imports from European countries such as Germany and Sweden. Given the USA's central role in the global forest products market, an examination of its wood product manufacturing industry offers valuable insights into both the domestic economy and broader global market dynamics.

Several structural shifts associated with the COVID-19 pandemic contributed to pronounced volatility in wood product prices. A central channel was the contraction in labor supply, particularly among less-skilled and semi-skilled workers, following the declaration of a national emergency and the implementation of restrictive public health policies. Albanesi and Kim (2021) classify occupations based on their flexibility to work remotely and contact intensity. Occupations in manufacturing, production, and transportation jobs are categorized as inflexible and low-contact, and the total employment in these sectors is estimated to experience a 30% decline in 2020. In addition, DeLuca and Pinheiro (2023) reports an uneven recovery across occupations and industries, with slower employment recovery observed in the construction, production, and transportation sectors. These disruptions in labor markets related to wood product manufacturing are likely contributing to the large swings in product prices during the pandemic period.

The labor market disruptions within the wood product manufacturing and transportation sectors are evident in the National Employment Statistics published by the U.S. BLS (BLS OEWS, 2022). Following the imposition of pandemic-related lockdowns, the total number of employees in the manufactured wood products industry declined from 405,300 to 373,700 workers, representing a 7.5% reduction. A comparable contraction occurred in the truck transportation sector, where employment decreased from 1,492,200 to 1,413,100 workers (BLS, 2020, 2021). The primary reason for this labor supply contraction was illness. According to estimates from the BLS's Survey of Occupational Injuries and Illnesses, the total number of reported illness cases in the private sector more than quadrupled in 2020, increasing from 127,200 cases in 2019–544,600 in 2020 (BLS, 2020). The significant rise in illnesses is mainly driven by a 4,000% increase in employer-reported respiratory illnesses, from 10,800 in 2019–428,700 in 2020 (BLS, 2021). Although employment levels eventually returned to pre-pandemic levels within months of the initial decline, the temporary labor shortages in transportation and wood manufacturing sectors led to supply chain stagnation, resulting in product shortages and subsequent price increases in the forest products market (Chizmar *et al.*, 2023). Over the longer run, employment actually surpassed pre-pandemic levels as the economy recovered.

In addition to labor market disruptions, shifts in consumer housing preferences have significantly driven the volatility in wood product prices. Over one-third of annual US softwood lumber and structural panel consumption is tied to new housing construction (Howard and Liang, 2019), making the surge in pandemic-induced housing demand a key factor in applying upward pressure on the demand for manufactured wood products. Economists have extensively studied the housing market's behavior during the pandemic, noting that the rise in remote work opportunities (Davis *et al.*, 2021) and "stay-at-home" shocks altered household consumption patterns, contributing to increased housing demand (Gamber *et al.*, 2023). Housing starts initially plummeted during the initial outbreaks of the pandemic. This reflected economic shutdowns and uncertainty. However, housing starts quickly rebounded in the third quarter of 2020 and by late 2020 had surpassed pre-pandemic levels (McCord, 2021). This is further reflected in private residential fixed investment (PRFI), a key indicator of private sector expenditures on fixed assets, which spiked significantly in 2020. According to the U.S. Bureau of Economic Analysis, PRFI rose from approximately $815bn in the second quarter of 2020 to a historic high of $1,218bn in the first quarter of 2022. While there has been a subsequent decline, the current estimated PRFI of $1,076bn still represents a 32% increase from the second quarter of 2020, underscoring the sustained strength of housing demand and its impact on the wood product market.

In this study, we assess the impact of the COVID-19 pandemic on the prices of three key manufactured wood products: SPF, Southern Yellow Pine (SYP) and OSB, using a vector error correction (VEC) model. Figure 1 presents the monthly price movements of these products from 1995 to 2023, with the onset of the pandemic marked by a

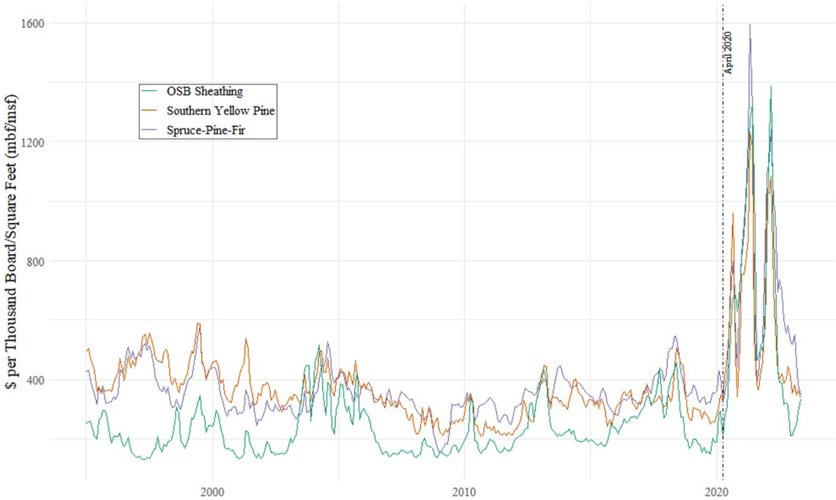


Figure 1. Price movements of spruce-pine-fir, Southern yellow pine and OSB sheathing

vertical dotted line. While prices have largely reverted to their pre-pandemic levels, it is clear that manufactured wood product prices experienced unprecedented volatility during the pandemic period. Motivated by these abnormal price fluctuations, this study attempts to quantify the extent to which the pandemic contributed to the observed volatility. To accomplish this, we divide the data set into pre- and post-pandemic subsets and conduct an event study to measure the pandemic's impact on price movements. We then assess the contribution of exogenous shocks from other sectors to the high volatility in wood product prices within the context of the COVID-19 pandemic. To do so, the constructed VEC model incorporates exogenous variables from multiple sectors closely linked to forest product markets, such as housing and labor markets. This approach provides a comprehensive representation of market dynamics, enabling us to disentangle the effects of sector-specific information on wood product prices. Impulse response functions are used to illustrate how individual wood product prices react to shocks originating from these related sectors.

Several studies have examined the impact of COVID-19 on forest products from different perspectives. For instance, Zanello *et al.* (2023) analyze lumber price movements in relation to multiple events, including the COVID-19 pandemic, the Great Financial Crisis of 2008, the Pacific Northwest floods in 2021, and the softwood lumber agreements of 1981 and 2006. Their findings indicate that while the pandemic significantly affected the softwood lumber industry, the magnitude of the impact was smaller compared to the disruption caused by the 2021 floods, which severely affected supply chains. Similarly, van Kooten *et al.* (2022) examine the welfare effects of the pandemic on the US lumber market, estimating that US lumber producers gained $5.3bn while US consumers lost $7.3bn per quarter during the pandemic. Gan *et al.* (2022) investigate the synchronized price movements between US lumber futures and southern pine saw-timber stumpage prices, analyzing their responses to various COVID-19-related events and economic stimuli. By using both a market model and an autoregressive integrated moving average model, they estimate the cumulative abnormal returns and reveal asymmetries in price adjustment and benefit distribution among different market participants. While these studies provide valuable insights into the forest product market's response to the pandemic, few have explored the industry using a multivariate framework, leaving room for further analysis of the interactions between prices and broader economic factors.

This study contributes to the literature by providing a novel approach to quantifying the impact of the pandemic through a multivariate time series analysis. The findings from our event study and impulse response analyses offer new insights into the pandemic's effects on market dynamics within the manufactured wood products sector. While the pandemic-induced volatility has largely subsided, our analysis highlights the lasting shifts in market expectations following such extreme events. These insights are intended to enhance the understanding of wood price behavior and the influence of sectoral shocks, offering valuable implications for researchers, policymakers, wood producers, contractors and other stakeholders.

2. Price transmission and the U.S.-Canada softwood lumber dispute

Price transmission has been extensively studied in economics, as it reflects both the efficiency and resilience of markets. Price adjustments serve as a critical signal through which markets respond to exogenous shocks, providing insights into underlying supply and demand dynamics. In many cases, direct observation of these market forces is challenging, leading economists to view prices as key observable variables that convey essential information about market conditions and adjustments.

Horizontal price linkage studies typically examine how the price of the same commodity is transmitted across different geographic locations at the same stage of the supply chain. The transmission of price shocks between markets serves as an indicator of the efficiency of arbitrage, grounded in the fundamental economic principle of the Law of One Price (LOP). In the absence of transaction costs, LOP proposes that regional markets share a unique price. Deviations from LOP may indicate less integrated markets and unstable trading relationships (Fackler and Goodwin, 2001). Spatial price linkages among various US forest products have been studied extensively, including for sawtimber (Ning and Sun, 2014), softwood lumber (Sun and Ning, 2014), OSB sheathing (Goodwin *et al.*, 2011), southern pine stumpage (Prestemon, 2003; Daniels, 2011) and paper (Zhou and Buongiorno, 2005; Tang and Laaksonen-Craig, 2007).

Horizontal price linkages are sometimes referred to as cross-commodity price transmission, which focuses on the relationships between the prices of different commodities within the same market or stage of the supply chain. This analysis often includes the examination of price co-movements, shedding light on the substitutability and complementarity between commodities. In this study, we examine whether the market for imported softwood lumber is integrated with the market for domestically produced wood products. To gain a more comprehensive understanding of the manufactured wood products sector, we include OSB sheathing, a key wood structural panel, in addition to SPF from Canada and SYP in the USA [1].

This study is motivated by the sharp rise in manufactured wood product prices during the COVID-19 pandemic and the broader context of the ongoing trade dispute between the USA and Canada. Because the products analyzed are among the most widely used inputs in the US construction industry, analyzing their price linkages offers valuable insights into the structure of forest product trade and informs policy decisions affecting the sector.

There has been a longstanding trade conflict between the USA and Canada over trade in softwood lumber products since 1982. In Canada, most softwood lumber comes from publicly-owned forests, which are managed by provincial governments. This is opposite to the USA, which has a higher share of privately owned forests. Due to this different regulatory framework, the US lumber producers petitioned the U.S. Department of Commerce to set a tariff on Canadian softwood lumber imports, as they argue that the Canadian government unfairly subsidizes the lumber sector. The US lumber industry claims that Canadian lumber producers for selling below cost, therefore, imposing unfair competition in the market. The U.S. government responded by imposing various trade restrictions on Canadian softwood lumber imports, including countervailing duties and anti-dumping duties (Zhang, 2007).

As of August 2024, the USA imposes import duties ranging from 8.05% to 14.54%, depending on the specific Canadian company (lumber manufacturer) (U.S. Department of Commerce, 2024). Canadian softwood lumber imports would be detrimental to the US lumber market only if the two products are related. That is, if the two lumber products are not related, then any trade restrictions on Canadian softwood would not affect US SYP markets. Several studies have analyzed the substitutability between the US and Canadian softwood lumber through a demand system. For instance, Nagubadi *et al.* (2004) use a restricted translog subcost function to softwood consumption and prices and find the SPF group appears to be substitutes for untreated SYP and structural panels. Similar results are also found by Gan (2006) that US domestic and imported forest products have become more substitutable over time. Shook *et al.* (2007) estimate the cross-price elasticity of demand of the US softwood lumber species and did not find strong evidence that Canadian softwood species behave as substitutes to the US domestic species. Our study takes on a different approach by examining the cross-commodity price transmission, in the hope of providing more insights from this perspective.

3. Econometric methods

Vector autoregressive (VAR) models are widely used in the analysis of multiple time series, providing a flexible framework for evaluating dynamic interactions among several variables. When the components of a VAR system are nonstationary, standard practice typically requires transforming the data, such as by taking differences, to achieve stationarity. However, differencing the data may distort long-run relationships if the variables are cointegrated, meaning they share a common long-term equilibrium. To address this issue, the VAR model can be reformulated to incorporate cointegration restrictions, resulting in a VEC model. This approach allows for the preservation of long-run equilibrium relationships while still accounting for short-term dynamics.

We begin our analysis by evaluating the time-series properties of each variable included in the models, followed by estimating models to examine the relationships among prices. First, we conduct stationarity and cointegration tests. To assess the presence of unit roots, we apply the standard augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), which is designed to detect nonstationarity in individual time series. In addition, we report test statistics from the Phillips-Perron (PP) test, which accounts for heteroscedasticity in the time series. Upon confirming the nonstationary nature of the data, we proceed by testing for cointegration using both the Engle-Granger and Johansen cointegration tests, allowing us to assess whether long-run equilibrium relationships exist among the variables.

A standard VEC model is of the form:

$$\Delta y_t = a + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + u_t \tag{1}$$

where Π and Γ_i are parameter matrices to be estimated.

Once the time-series properties are defined, we implement an extended VEC model. The standard VEC system describes the joint generation process of all variables within the system. However, in practice, the dynamics of the system may be influenced by factors outside of it. Given that wood product prices are affected by exogenous factors from other sectors, we extend the basic VEC model to include a set of exogenous variables. In addition, we incorporate seasonal dummies, treated as non-stochastic exogenous variables, to account for potential seasonal effects. The extended model specification is as follows:

$$\Delta y_t = a + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \sum_{i=1}^{s} B_i x_{t-s} + \epsilon_t \tag{2}$$

where x_t is the vector of all deterministic terms and B_i are the corresponding coefficient matrices. s is the number of lags for exogenous variables [2]. Finally, ϵ_t is the error term with mean zero and variance-covariance matrix Σ.

Following model estimation, we conduct an event study to compare the forecasted results from the econometric models with observed values, allowing us to assess abnormal price movements in the wood product market. An event study is a statistical tool originally developed in finance and accounting to examine the impact of specific events on financial assets (MacKinlay, 1997), which has since been widely adopted in economics. In the context of this study, we compare the model's forecasted prices with observed wood product prices following the pandemic. Prices that fall outside the expected forecast bands are considered abnormal, indicating significant deviations attributable to the event. In addition, we evaluate the dynamic patterns of price adjustment in response to shocks from exogenous variables by employing impulse response functions. These functions provide a clear representation of both the magnitude and persistence of price reactions to specific shocks, offering insights into the underlying adjustment mechanisms within the market.

4. Empirical analysis

We focus on three of the most commonly used manufactured wood products in the U.S. construction industry: two types of softwood lumber, SPF and SYP, and one structural sheathing product, OSB. SPF lumber refers to a grouping of spruce, pine and fir species, which exhibit similar physical and mechanical properties, leading to their common harvesting and processing. SYP encompasses native pine species predominantly found in the southern USA, with four species, loblolly, shortleaf, longleaf and slash pine, accounting for 90% of the southern pine timber industry (AIFP Lumber, 2019). As the largest softwood product produced in the USA, SYP is primarily used in housing framing and outdoor construction, including fencing and decking. OSB, an engineered structural panel made by cutting wood strands from small logs, is mainly utilized as a load-bearing structural component in roofs, walls, and floors. Price trends for these forest products are shown in Figure 1.

We utilize end-of-week prices for 2 × 10 kiln-dried Western SPF lumber from Western Canada, 2 × 10 kiln-dried SYP lumber from the western USA, and 7/16-in. OSB sheathing from the Southwest US region. To analyze the influence of shocks from other sectors on the manufactured wood product industry, we incorporate six exogenous variables into our model. Given the strong connection between wood product markets and the US construction industry, we include data on new privately owned housing starts, sourced from the U.S. Census Bureau and the U.S. Department of Housing and Urban Development. To capture potential labor market disruptions, we integrate wood product manufacturing employment data from the BLS. In addition, we account for broader economic conditions using the Industrial Production Index

(IPI), which tracks production levels and capacity utilization rates across manufacturing, mining, and utility sectors (Federal Reserve Board, 2017), with data provided by the Board of Governors of the Federal Reserve System.

Copper and aluminum are extensively used in construction and other industries, making their price fluctuations potentially influential on the prices of manufactured wood products, though the reverse is unlikely. For this analysis, we use three-month rolling forward contract prices for both metals from the London Metal Exchange (LME), with data sourced from Bloomberg. Similarly, energy market fluctuations can impact wood product prices due to the industry's heavy reliance on domestic trucking for supply. The crude oil market experienced significant supply-side disruptions during the COVID-19 pandemic, with West Texas Intermediate (WTI) crude oil prices plunging in Spring 2020 and briefly turning negative in April 2020, followed by a rapid recovery later in the year. Given these dynamics, we examine the effect of crude oil price changes on the selected wood products. WTI crude oil, a global benchmark, is measured using free-on-board spot prices, collected from the U.S. Energy Information Administration. Table 1 provides a comprehensive overview of data sources and detailed information on all variables. Each price series is adjusted for inflation using the Consumer Price Index (CPI) from the BLS. All time-series data are collected monthly from January 1995 to May 2023.

To compare price behavior before and during the pandemic, we divide the data set into two estimation windows. March 20, 2020, is identified as the onset of the pandemic, marking the implementation of lockdown measures in the USA. As a result, our pre-pandemic period includes monthly data from January 1995 to March 2020, while the event period spans from April 2020 to May 2023. Summary statistics for both periods are presented in Table 2. It is unsurprising that the average prices of all three wood products surged during the pandemic period. Notably, OSB sheathing prices experienced the largest increase, averaging a 170% rise, followed by SPF at 102%, and SYP at 67%. In addition, there was a marked increase in the standard deviation of wood product prices during the pandemic, indicating heightened price volatility during this period.

Copper and aluminum prices also exhibited significant increases, while crude oil prices showed a moderate rise. Despite an initial sharp decline in employment due to the pandemic, the summary statistics do not indicate an overall reduction in employment levels over the event period. Furthermore, we observe an increase in the number of residential housing starts during the pandemic. As highlighted in the plots in Figure A1, certain processes, such as housing starts and employment, exhibit strong

Table 1. Variable descriptions and data source

Variable	Descriptions	Data source
Spruce-pine-fir	$/Thousands board-feet	Random Lengths, part of Fastmarkets
Southern yellow pine	$/Thousands board-feet	Random Lengths, part of Fastmarkets
OSB sheathing	$/Thousands Square Feet	Random Lengths, part of Fastmarkets
Aluminum	LME 3-month rolling forward, $/ton	Bloomberg
Copper	LME 3-month rolling forward, $/ton	Bloomberg
Crude oil	WTI crude oil, $/barrel	U.S. Energy Information Administration
Housing starts*	Thousands of units	U.S. Census Bureau, U.S. Department of Housing and Urban Development
Employment*	Thousands of persons	U.S. Bureau of Labor Statistics
IPI*	Industrial production index, 2007 = 100	Board of Governors of the Federal Reserve System (U.S.)
CPI*[1]	Consumer price index for all urban consumers, 1982–1984 = 100	U.S. Bureau of Labor Statistics

Note(s): *Data retrieved from FRED, Federal Reserve Bank of St. Louis. [1]CPI is used to deflate all prices for the analysis

seasonal patterns, emphasizing the need to account for seasonality in the model to isolate nonseasonal patterns critical to the analysis.

Our objective is to select a parsimonious model that effectively characterizes the dynamics of the system. The model selection process is guided by several key considerations. First, we assess the time-series properties of the variables to determine stationarity and cointegration. Before conducting unit root tests, we identify the optimal lag length for the model by considering a maximum of 16 lags, given that our

Table 2. Summary statistics, before and after April 2020

Variable	Pre-pandemic (Jan. 1995–Mar. 2020)					Event period (Apr. 2020–May 2023)				
	N	Mean	St. dev.	Min.	Max.	*N*	Mean	St. dev.	Min.	Max.
Spruce-pine-fir	303	353.36	69.47	155.25	582.60	38	714.58	308.32	329.50	1592.50
Southern yellow pine	303	351.96	81.77	209.50	588.50	38	588.86	265.13	326.75	1234.00
OSB sheathing	303	227.85	80.37	132.50	515.20	38	613.38	346.87	205.50	1386.25
Aluminum	303	1859.28	419.89	1186.50	3114.00	38	2371.58	471.42	1494.50	3491.00
Copper	303	4715.26	2499.59	1374.00	9885.00	38	8386.03	1353.89	5188.50	10375.00
Crude oil	303	53.13	28.92	11.35	133.88	38	70.16	23.54	16.55	114.84
Housing starts	303	109.53	38.58	31.90	197.90	38	125.90	17.53	84.90	164.30
Employment	303	753.10	124.10	528.00	1037.30	38	876.28	53.83	697.80	945.90
IPI	303	93.31	8.39	69.86	106.08	38	99.32	4.67	82.64	104.81

Note(s): Data frequency is monthly

pre-pandemic sample contains 303 observations [3]. Stationarity tests reveal the presence of a single unit root in all cases, with each series becoming stationary after first differencing, indicating that all series are integrated of order one [4].

Next, we test for cointegration among the three endogenous variables using the two-step procedure of Engle and Granger and the trace test proposed by Johansen. Since the Engle and Granger method tests for cointegration between two variables, we apply the test to all three possible pairs of wood products. The test statistics are presented in Table 3, where the rejection of the ADF test in all cases suggests the presence of cointegration. However, Johansen's trace test indicates three cointegration relationships within the system, equal to the number of endogenous variables. This finding suggests stationarity of the processes, contradicting the results from the two-step procedure and the unit root tests.

Sims *et al.* (1990) demonstrate that an unrestricted VAR in levels (VARL) provides consistent estimates when the data are cointegrated, without requiring the explicit determination of cointegration relationships. Similarly, Suharsono *et al.* (2017) and Zhang *et al.* (2010) show that fitting a VARL model can yield superior out-of-sample forecasting performance compared to models with imposed cointegration constraints. To evaluate model performance, we compare their out-of-sample fit using three forecasting accuracy metrics: root mean squared error (RMSE), mean absolute percentage error (MAPE) and Theil's U statistic:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(A_t - F_t)^2} \tag{4}$$

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{A_t - F_t}{A_t}\right| \tag{5}$$

Table 3. Cointegration test statistics

	Engle and Granger's two-step procedure		Johansen's trace test		
Commodity pair	ADF tau	*p*-value	Null hypothesis (r)	Test statistics	*p*-value
SPF-SYP	−5.09	<0.0001	H_0: r = 0	95.34	<0.0001
SPF-OSB	3.54	0.0005	H_0: r = 1	49.02	<0.0001
SYP-OSB	−2.841	0.0046	H_0: r = 2	15.07	0.0002

Table 4. Forecasting accuracy metrics comparisons

Variable	Model	RMSE	MAPE	Theil's U
Spruce-pine-fir	VARL(2, 0)	0.475	0.066	0.087
	VEC(2, 0)	0.452	0.061	0.083
Southern yellow pine	VARL(2, 0)	0.477	0.063	0.090
	VEC(2, 0)	0.473	0.065	0.089
OSB sheathing	VARL(2, 0)	0.740	0.108	0.140
	VEC(2, 0)	0.832	0.129	0.158

$$Theil^{'}sU = \sqrt{\frac{\sum_{t=1}^{N-1}\left(\frac{F_{t+1} - A_{t+1}}{A_t}\right)^2}{\sum_{t=1}^{N-1}\left(\frac{A_{t+1} - A_t}{A_t}\right)^2}} \tag{6}$$

where A is the actual value, F is the forecasted and $N = 38$. Unlike RMSE and MAPE, which emphasize the magnitude of the forecast error, Theil's U statistics compare the model's forecast to naive guessing. If Theil's U statistic is less than 1, then the forecasting technique is better than guessing. Comparison of forecasting accuracy metrics is in Table 4. Overall, the VEC model gives better out-of-sample forecasts for the two lumber products, whereas VARL does a better job predicting OSB sheathing [5].

5. Empirical results

To empirically assess the impact of the COVID-19 pandemic on the manufactured wood industry, we conduct an event study by comparing the forecasted wood product prices generated by the specified VEC(2,0) model to the observed prices during the pandemic period. Prior to analysis, the time-series data are log-transformed. We define March 20, 2020, as the event start date, immediately following the declaration of COVID-19 as a national emergency. This date is marked by a vertical line in Figure 1, indicating a clear shift in behavior across all variables. To confirm the presence of a structural break around this date, we perform a Chow test (Chow, 1960), with results in Table 5 showing a significant structural break in all price series at the onset of the pandemic.

The event study results are presented in Figure 2, where the forecasted prices are plotted alongside the observed prices during the event period. Several important observations are worth noting from the graphs. First, the model performs well in the pre-pandemic period, with fitted values closely matching observed prices. However,

Table 5. Chow structural break test[1]

Variable	Date of structural break	F statistics	*p*-value
Spruce-pine-fir	4/1/2020	128.86	0.00
Southern yellow pine	4/1/2020	135.72	0.00
OSB sheathing	4/1/2020	116.34	0.00

Note(s): [1] H_0: There is no breakpoint at the defined date

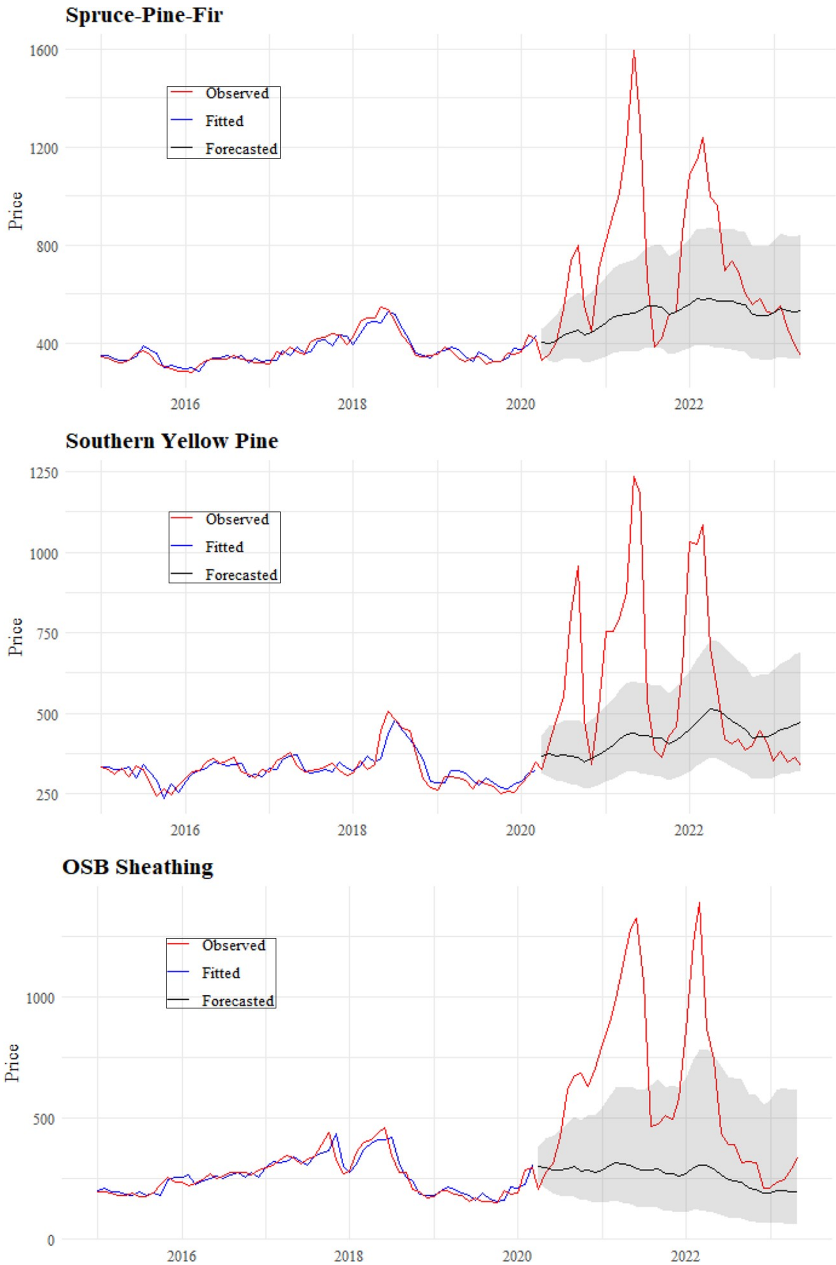


Figure 2. Expected and actual price movement during the event period

Note(s): The shaded area represents the 95% confidence band. The red line indicates the actual observed price, blue line indicates the model fitted values, and the black line is the model forecasted values. The event period is from April 2020 to May 2023. Forecasts are based on a VEC(2, 0) model, forecasting period is 38 months despite accounting for potential structural changes from related sectors, the model fails to capture the extreme price volatility observed during the pandemic, as actual prices deviate significantly from the forecasts. This confirms the unprecedented price volatility in the manufactured wood product markets caused by the pandemic.

Notably, spikes in wood product prices correspond to peaks in COVID-19 death rates, as shown in Figure A2, though this correspondence could be coincidental and does not necessarily suggest a causal link. Weekly COVID-19 death rate data from the Centers for Disease Control reveal a close correlation, with spikes in death rates lagging behind increases in SYP prices by approximately four months. Furthermore, all three wood product prices returned to their expected levels approximately three years into the pandemic, suggesting that while the shocks were transitory, their effects were long-lasting.

In addition, one of the major price surges observed during the sample period coincided with the November 24, 2021, announcement of a tariff increase on Canadian softwood lumber, as shown in Figure 3. Trade policy between the USA and Canada has historically played a central role in shaping softwood lumber prices. The data suggest that market responses to tariff changes vary depending on broader economic conditions. Figure 3 highlights two major tariff increases since the expiry of the Softwood Lumber Agreement in 2015. The first occurred on April 24, 2017, when the U.S. Department of Commerce announced new countervailing duties averaging 20% on Canadian softwood lumber imports, affecting approximately $5bn in trade or 31.5% of the US market (Reuters, 2017). This announcement led to a noticeable price disparity between Canadian and US markets. In contrast, the 2021 tariff increase,

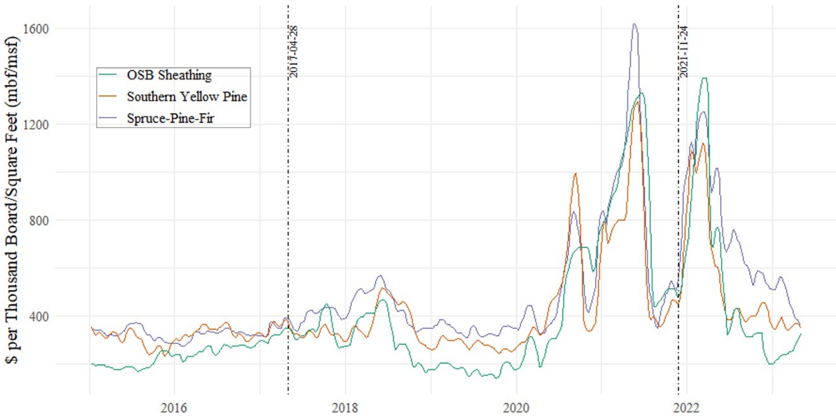
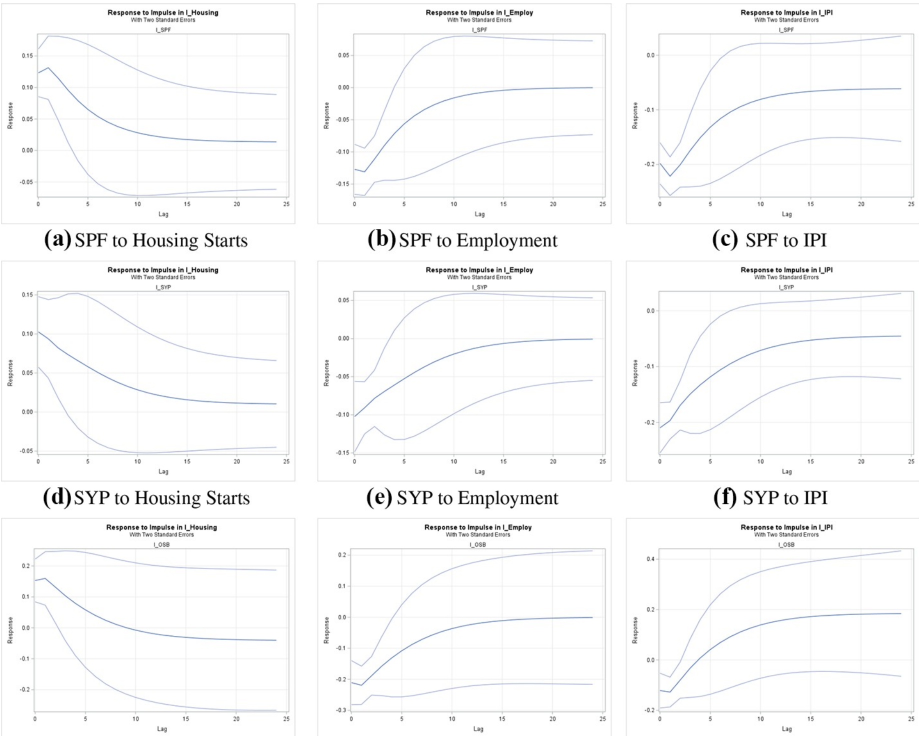


Figure 3. Changes in wood product price when tariff increased in 2017 and 2021

raising rates to 17.99% from the prior 8.99% set under the Trump administration, was associated with a sharp price increase rather than a decline. This suggests that during the pandemic, tariffs may have had a more pronounced effect on US wood product prices.

To quantify the magnitude and direction of the pandemic's impact across different sectors, we conduct an impulse response analysis, with the results displayed in Figure 4. These plots display the impulse responses of the three manufactured wood products to a one percent shock in the exogenous variables. Several key observations emerge from this analysis. First, all three wood product prices respond significantly to shocks from housing starts, employment in the manufactured wood sector, and the IPI. These effects are transitory, with prices returning to near-equilibrium levels within



(a) SPF to Housing Starts **(b)** SPF to Employment **(c)** SPF to IPI

(d) SYP to Housing Starts **(e)** SYP to Employment **(f)** SYP to IPI

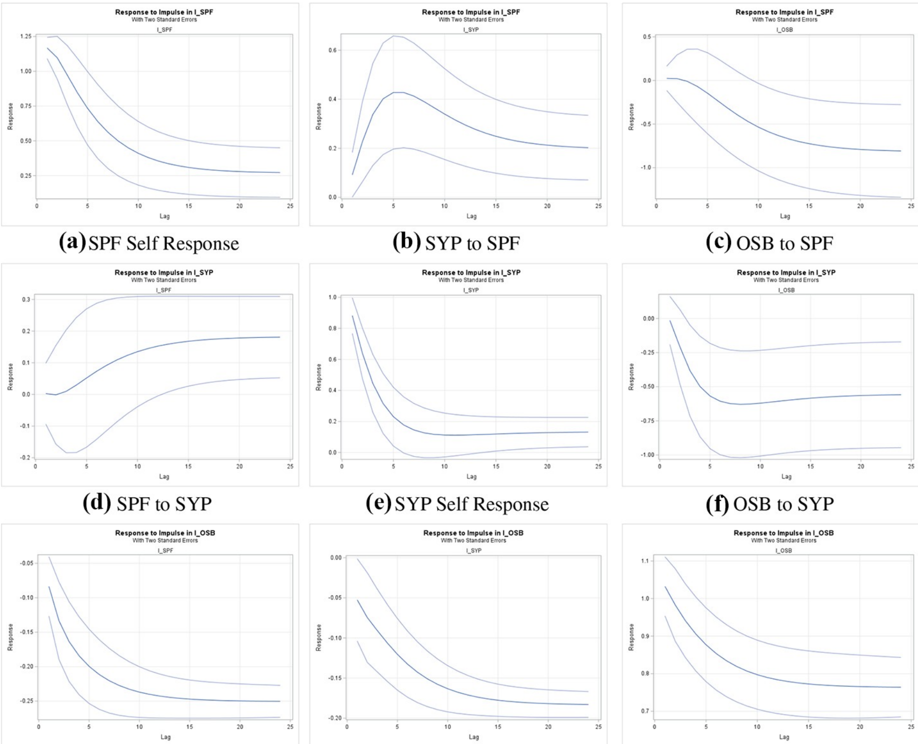
(g) OSB to Housing Starts **(h)** OSB to Employment **(i)** OSB to IPI

Figure 4. Impulse responses of wood product prices to shocks from exogenous variables

Note(s): Panels (a)–(c), (d)–(f) and (g)–(i) present SPF, SYP and OSB's responses to a shock from Housing Starts, Employment and IPI, respectively. Responses are generated based on a VEC(2, 0) model with seasonal dummies. The data frequency is monthly. All variables are transformed into natural logs

12 months. In contrast, there are no significant responses to shocks from copper, aluminum and crude oil prices (see plots in Figure A3), suggesting that the dynamics in the energy market and the metal market do not contribute much to price swings in wood product prices.

The directions of the responses are consistent with expectations. Wood product prices respond positively to increases in housing starts, which reflects that increases in housing demand subsequently drive up the demand for wood products, thereby driving up prices. On the other hand, prices respond negatively to increases in employment in the manufactured wood sector, which aligns with economic intuitions that increased labor supply increases production capacity, thereby applying downward pressure on prices (and upward pressure on prices when workers exit the workforce during the



(a) SPF Self Response **(b)** SYP to SPF **(c)** OSB to SPF

(d) SPF to SYP **(e)** SYP Self Response **(f)** OSB to SYP

(g) SPF to OSB **(h)** SYP to OSB **(i)** OSB Self Response

Figure 5. Impulse responses of wood product prices to shocks from each other

Note(s): Panels (a)–(c), (d)–(f) and (g)–(i) present responses to a shock from SPF, SYP and OSB, respectively. Responses are generated based on a VEC(2, 0) model with seasonal dummies. The data frequency is monthly. All variables are transformed into natural logs pandemic due to illness and other factors (see Chizmar *et al.*, 2023). The significant negative relationship between manufactured wood product prices and the labor market reflects a labor-focused dynamic within wood product markets. Producers may prioritize investments in manufacturing technologies or innovations to mitigate the impact of potential labor market contractions and external shocks, such as those induced by the pandemic.

Overall, the impulse response analysis suggests that in the short run, manufactured wood product markets are subject to significant structural adjustments driven by labor supply changes, housing demand shifts and broader economic conditions. While these effects are substantial, they are transitory, with the market typically adjusting within a one-year timeframe.

An additional aspect of the analysis involves examining the interrelationships between the three wood products. Impulse response results are presented in Figure 5. We observe that SYP prices respond positively to a shock in SPF prices, whereas SPF prices do not react to an increase in SYP prices. This indicates a one-way substitution effect, where SYP treats SPF as a substitute, but SPF does not reciprocate. In addition, OSB prices respond negatively to positive shocks in both lumber products, and vice versa, indicating a complementary relationship between sheathing and softwood lumber in the construction sector.

6. Discussion and conclusions

The US manufactured wood industry has experienced unprecedented price volatility since the onset of the COVID-19 pandemic, with significant fluctuations persisting even three years after the pandemic was declared. Given the strong relationship between wood product prices and changes in the labor and housing markets, studying this sector is crucial for understanding broader economic recovery and growth. The sharp variations in wood prices during this period increased risks and uncertainty for stakeholders in the construction industry and posed challenges for policymakers seeking to implement effective recovery measures.

This study examines the impact of the pandemic on three key manufactured wood products (SPF, SYP and OSB) using an event study approach. Forecasted values are derived from a VEC model that incorporates exogenous variables. The results of the event study reveal that wood product prices deviated significantly from the model's expected values during the pandemic. However, our findings suggest that these prices returned to their pre-pandemic levels after approximately three years.

Understanding the price behaviors of manufactured wood products in response to external shocks is crucial, as the forest industry reflects the general economy's supply and demand dynamics, making it a valuable economic indicator. By incorporating exogenous variables, we can examine how shocks in related sectors transmit through wood product prices using impulse response analysis. Our results indicate that all three wood product prices respond positively to increases in housing starts and negatively to increases in employment within the wood manufacturing sector. These results align with our hypothesis that disruptions in labor and housing markets played a significant role in explaining the abnormally volatile wood product prices during the pandemic.

Furthermore, given that a substantial portion of domestically consumed softwood lumber is imported, lumber price movements have critical implications for trade policy, particularly in the context of the ongoing U.S.-Canada softwood lumber dispute. Our analysis of cross-commodity price transmission provides insights into market resilience and price signal pass-through between U.S. and Canadian markets. We find that SYP produced in the U.S. views SPF imported from Canada as a substitute, while SPF does not respond similarly to changes in SYP prices. Also, OSB sheathing behaves as a complement to both lumber products. These findings offer important insights for future analyses of U.S.-Canada lumber trade dynamics.

While some long-run effects of the pandemic may remain unidentified, the majority of the pandemic-induced market volatility has diminished. Evidence suggests that the manufactured wood product industry adjusts to significant external shocks within a three-year timeframe. However, further analysis extending to five years post-pandemic would be beneficial to ensure that any lingering effects have fully dissipated. Our analysis could be extended to include additional lumber species and related wood products. Our methodology can also be applied to other international trade commodities to examine the relationships between imported and domestically produced products.

Notes

[1.] While plywood sheathing also competes with OSB in this market, our analysis indicates that its inclusion does not add significant dynamics to the model. More precisely, the impulse response analysis shows that shocks to plywood prices have an insignificant effect on the other three manufactured wood products, leading to their exclusion from the study.

[2.] It is possible that $s = 0$, which is assumed for this study. It is appropriate not to include these variables in the cointegration relations, as we assume the lag order of exogenous variables is 0. This implies that only the current value of the exogenous variables would affect the current endogenous variables.

[3.] The optimum lag is determined using a rule of thumb suggested by Schwert (1989):

$$p_{max} = \left[12 \left(\frac{T}{100} \right)^{1/4} \right] \quad (3)$$

[4.] Stationarity test results are presented in Table A4. The exogenous variables also display unit roots across all tests.

[5.] Additional discussions on model specification are presented in Appendix 1. We also evaluated the performance of a Bayesian approach using Minnesota priors (Litterman, 1986), which has demonstrated success in macroeconomic forecasting and other fields (Bergman et al., 2017; Karlsson, 2013). The implementation details and results are provided in Appendix 2. In summary, the Bayesian models produced forecasts that were either comparable to or slightly better than those of the classical models, as shown in Table A3. However, the differences in the forecasting accuracy metrics were not substantial. Given the increased computational complexity and reduced interpretability of the Bayesian models, we opted for the more straightforward VEC model, which includes exogenous variables, as the most appropriate specification for our analysis. Overall, we conclude that the classic VEC model with exogenous variables provides the best balance for this study. Ultimately, we select the VEC(2, 0) specification for our subsequent empirical analysis.

[6.] Note that a VEC(p) model has an equivalent VAR(p). Please see Appendix 1 for details.

[7.] Models with longer and shorter lag length are examined, although the diagnostic results are not included in the table as these models do not appear to give a better fit than the two models presented here.

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Appendix 1. Additional discussions on model specifications

Since unrestricted VAR in levels (VARL) can produce consistent estimates of cointegrated data, we investigate both VARL and VEC models and compare their performance. One important component of model specification for time series models is to select the correct number of lags. In addition, our model involves several exogenous variables, which also require lag selection. There is not much guidance in the literature on how to select lags for exogenous variables. Therefore, we choose the model that generates the lowest information criterion. We use three types of information criteria to determine the best model fit, namely the corrected Akaike Information Criterion (AICC), Bayesian Information Criterion (BIC) and Hannan-Quinn Criterion (HQC). The calculated information criteria are presented in Table A1 [6]. We can see that model VEC(2, 0) is the most appropriate, given it minimizes all three information criteria [7]. We implement another model diagnostic check, which is the Portmanteau test, to see whether correlations remain in the model residuals. The test results are presented in Table A2. The null hypothesis of the Portmanteau test is that all autocorrelations and cross-correlations in the residuals are

Table A1. Goodness-of-fit comparison across models

Information criterion	VARL(2, 0)	VARL(2, 1)	VEC(2, 0)	VEC(2, 1)
AICC[1]	−3537.83	−3501.70	−3544.16	−3512.47
BIC[2]	−3304.18	−3237.11	−3323.36	−3256.83
HQC[3]	−3477.63	−3450.59	−3483.46	−3456.97

Notes(s): [1]AICC: Corrected Akaike Information Criterion; [2]BIC: Bayesian Information Criterion; [3]HQC: Hannan-Quinn Criterion (HQC)

Table A2. Portmanteau test for cross correlations of residuals

	VEC(2, 0)	
Up to lag	Chi-square statistics	*p*-value
3	22.47	0.008
4	24.96	0.126
5	40.38	0.047
6	44.94	0.146
7	52.00	0.220
8	59.99	0.268
9	71.81	0.209
10	79.83	0.247

Note(s): H_0: All auto-correlation and cross-correlations are zero

zero. Looking at the *p*-values, the null hypothesis is rejected only for the third and fifth lag, and all other lags are uncorrelated, implying that VEC(2,0) is the appropriate model.

Appendix 2. Bayesian approach

Bayesian methods have demonstrated great success in forecasting in many fields (Bessler and Kling, 1986; Xie *et al.*, 2014; Bergman *et al.*, 2017). We implement a Bayesian approach to both VAR and VEC models to explore the possibility of better model performance. In this Appendix, we first briefly explain Bayes' theorem, which is the fundamental building block for any Bayesian approach. We then present the prior selection process, then calculate the forecasting accuracy metrics for this method. We find that when forecasting manufactured wood products, the Bayesian approach only slightly improves the forecast in some cases. Therefore, considering its calculation complexity and low interpretability, we conclude that the Bayesian approach is not suitable for the context of this study.

Bayes' theorem

Bayes' theorem is the foundation of any Bayesian modeling. In the Bayesian approach, nonsample information, or prior density, is given in the form of a density. Here, we provide a detailed discussion of Bayes' theorem and how prior distribution is selected in the applied empirical analysis.

Given two dependent Events A and B, the probability of Event B occurring conditional on Event A can be written as:

$$p(B|A) = \frac{p(B \cap A)}{p(A)} \tag{B1}$$

Similarly, the conditional probability of Event A occurring given Event B is:

$$p(A|B) = \frac{p(A \cap B)}{p(B)} \tag{B2}$$

Since $A \cap B = B \cap A$, we can rewrite equation (2) as:

$$p(A|B) = \frac{p(B|A)p(A)}{p(B)} \tag{B3}$$

which is the well-known Bayes' rule. This rule can be extended to model estimation. Given data set x and model parameters θ, the Bayes' rule can be written as:

$$p(\theta|x) = \frac{p(x|\theta)p(\theta)}{p(x)} \tag{B4}$$

which is often simplified to:

$$p(\theta|x) \propto p(x|\theta)p(\theta) \tag{B5}$$

where $\propto$ means proportional to. We can drop the term $p(x)$ since the probability of the data set does not depend on θ. The term $p(\theta|x)$ is the probability of model parameters computed conditional on the data set x, in Bayesian terms, the posterior distribution. The term $p(\theta|x)$ represents the likelihood function, which gives the probability of the data conditional on the parameters. Finally, $p(\theta)$ is the prior distribution, where careful identification is needed based on background knowledge. In summary, the posterior distribution is proportional to the likelihood function multiplied by the prior distribution.

Implementation of BVEC model

The Bayesian method imposes prior beliefs to achieve a parametrically parsimonious model while still preserving rich patterns between time series, which could be more appropriate when modeling nonstationary data. In the generalized VAR model, the number of coefficients to be estimated is $n^2p + nk$, where n is the number of variables included in the VAR model, p is the lag order, and k is the number of deterministic variables. Even with a modest selection for variable and lag selections, the VAR model is still very likely to be overfit. The lack of degrees of freedom in a Bayesian framework is no longer an issue since the model would include relevant variables along with the prior information that reflects one's knowledge about the value of the coefficient, which minimizes the mean squared error loss function (Litterman, 1986).

The essence of the Bayesian method lies in incorporating prior beliefs to reduce the influence of certain coefficients. Litterman (1986) suggests that instead of just relying on economic theory to extract useful information, one can focus on the prior that gives the best out-of-sample forecast. If some information is useful for the future, it is likely to be useful for the past. Compared to the prior information that only focuses on the existing data, information that is spread across a wider spectrum is better. We adopt the prior that Litterman introduces, namely Minnesota (Litterman) price, for this analysis. Such a prior assumes the mean coefficient of 1 for the first own-lag and a prior mean of 0 on all other variables. This implies an assumption of a univariate random walk model for each of the time series. The prior variance is given by:

$$v_{ij,L} = \begin{cases} \left(\frac{\lambda}{L}\right)^2 & \text{if} \quad i = j \\ \left(\frac{\lambda\theta\sigma_{ii}}{L\sigma_{jj}}\right)^2 & \text{if} \quad i \neq j \end{cases} \tag{B6}$$

where λ is the standard deviation of the first own-lag, a large λ implies prior information is diffused. θ represents the tightness of other variables, and is bounded between 0 and 1. The larger the θ, the more information is given by the other variables. L is the number of lags, which is 2 selected using the Schwarz Bayesian criterion. Finally, σ_{ii} is the i^{th} diagonal element of Σ_u.

We follow Litterman's (1986) suggestion to choose the pair of the two hyperparameters, λ and θ, that provides the best out-of-sample forecast. To achieve this, we conduct a grid search across the range from 0 to 1 with a granularity of 0.1 for each hyperparameter. We compare the forecasting performance of a total of 100 possible parameter pairs for BVEC models. The corresponding accuracy metrics are presented as follows.

A comparison of forecasting accuracy across all three models for each of the wood products is presented in Table A3. The insignificant differences between the Bayesian approach and the standard models do not provide convincing evidence to conclude that a Bayesian approach with Minnesota priors provides a better forecast. Since priors are often subjective and Bayesian analyses are more complex and computationally challenging, we think the standard VEC model is the best approach to forecast SPF softwood lumber prices given our model setting.

Table A3. Forecasting accuracy comparison with Bayesian models

Variable	Model	RMSE	MAPE	Theil's U
Spruce-pine-fir	VAR(2, 0)	0.475	0.066	0.087
	BVAR(2, 0)	0.469	0.065	0.086
	VECM(1, 0)	0.452	0.061	0.083
	BVEC(1, 0)	0.445	0.060	0.081
Southern yellow pine	VAR(2, 0)	0.477	0.063	0.090
	BVAR(2, 0)	0.480	0.063	0.091
	VECM(1, 0)	0.473	0.065	0.089
	BVEC(1, 0)	0.473	0.065	0.089
OSB sheathing	VAR(2, 0)	0.740	0.108	0.140
	BVAR(2, 0)	0.757	0.110	0.144
	VECM(1, 0)	0.832	0.129	0.158
	BVEC(1, 0)	0.832	0.129	0.158

Appendix 3. Additional figures and tables

Figure A1. Time-series plots for all exogenous variables

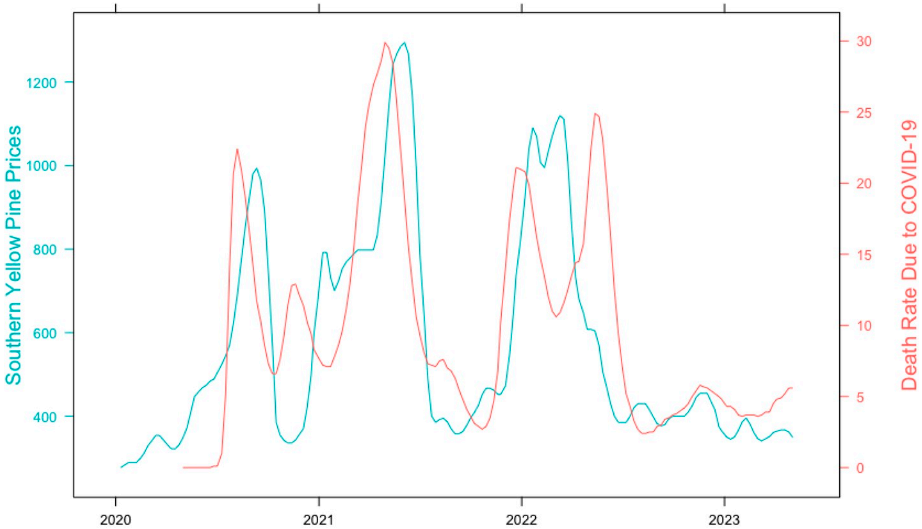

Figure A2. Southern yellow pine prices and percentage of deaths due to COVID-19

Note(s): This figure overlays Southern Yellow Pine prices with death rates due to the COVID-19 pandemic. The data frequency is weekly

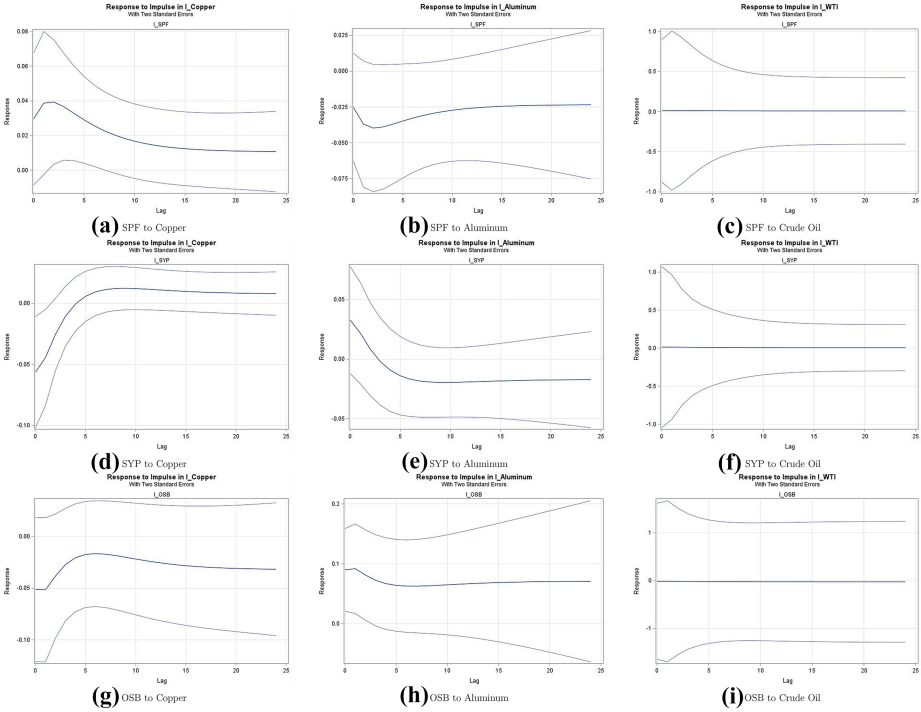

Figure A3. Impulse responses of wood product prices to shocks from exogenous variables
Note(s): Panels (a)–(c), (d)–(f) and (g)–(i) present SPF, SYP and OSB's responses to a shock from copper, aluminum and crude oil, respectively. Responses are generated based on a VEC(2, 0) model with seasonal dummies. The data frequency is monthly. All variables are transformed into natural logs

Table A4. Augmented Dickey-Fuller and Phillips-Perron unit root tests[1]

Variable	Optimal Lag[2]	ADF tau statistics	ADF *p*-value	PP tau statistics	PP *p*-value
Level data					
Spruce-pine-fir	2	−0.514	0.493	−0.564	0.472
Southern yellow pine	1	−0.740	0.396	−0.743	0.395
OSB sheathing	2	−0.463	0.514	−0.431	0.526
Aluminum	1	−0.830	0.357	−1.031	0.272
Copper	3	−0.096	0.650	−0.113	0.645
Crude oil	2	−0.452	0.518	−0.311	0.573
Housing starts	15	−0.259	0.593	−0.013	0.678
Employment	15	0.111	0.718	0.565	0.838
IPI	16	0.934	0.907	1.303	0.952
First difference					
Spruce-pine-fir	1	−11.954	<0.0001	−14.427	<0.0001
Southern yellow pine	0	−16.334	<0.0001	−16.337	<0.0001
OSB sheathing	2	−10.738	<0.0001	−15.172	<0.0001
Aluminum	0	−17.308	<0.0001	−17.307	<0.0001
Copper	0	−15.475	<0.0001	−15.463	<0.0001
Crude oil	1	−9.084	<0.0001	−12.119	<0.0001
Housing starts	14	−2.420	0.015	−16.463	<0.0001
Employment	14	−2.095	0.035	−7.685	<0.0001
IPI	15	−3.902	<0.0001	−26.319	<0.0001

Notes(s): [1]Unit root tests are performed on pre-pandemic data (Jan. 1995-Mar. 2020). The null hypothesis is the same fortwo tests. H_0: The time series contains a unit root; [2]Optimal lags are selected according to minimized Schwarz Information Criterion; the upper bound maximumnumber of lag used is 16. It is determined using Schwert's (1989) rule of thumb; [3]PP test must be performed with a minimum of 1 lag. Therefore, for variables that have an optimal lag length of 1, the test is performed with 1 lag