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Impacts of COVID-19 pandemic policies on timber markets in the Southern United States

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ABSTRACT

The global pandemic, due to SARS-CoV-2 (COVID-19), disrupted global commodity markets and individual consumption patterns. Various COVID-19-related policies were put in place by state and local governments to limit the virus outbreak, which disrupted the production and supply chains of manufacturing industries. The forest sector was not an exception. Using the Time Regression Discontinuity (T-RD) approach, we quantified the effect of various COVID-19 policies on standing timber prices in the Southern United States. We found an overall significant decrease in prices across all timber products (7%-30%) soon after COVID-19 lockdowns were implemented in early 2020. Findings from the fixed effects (FE) estimators suggest mandatory lockdowns for all individuals in certain areas of the jurisdiction had a decreasing price effect on pine pulpwood but an increasing effect on hardwood sawtimber. We expect that the findings from this study may help to set expectations for future market shocks if policies are implemented that impact the timber supply chain and consumer behavioral changes.

INTRODUCTION

The global infection, due to SARS-CoV-2 (COVID-19), was declared a pandemic by the World Health Organization on March 11, 2020 (Cucinotta and Vanelli 2020). In the two years from March 2020 to February 2022, over 97 million people were infected, and over 1 million people died due to the pandemic in the United States (U.S.), with an estimated 62% of the avoidable deaths due occurring in the U.S. South since the beginning of recorded infections (Johns Hopkins University and Medicine 2022; Stoto et al. 2021). Many consider the beginning of the pandemic in the U.S. to be late March 2020 (Prestemon and Guo 2022; van Kooten and Schmitz 2022), because illness began to spread more widely, and consumer preferences began to change.

COVID-19-related policies were put in place by state and local governments because no pharmaceutical treatment was initially available. Thus, non-pharmaceutical interventions, such as social distancing and stay-at-home policies (also known as “shelter in place” policies or “lockdown” policies), were adopted by local governments in hopes they would prevent healthcare systems from being overwhelmed with an influx of patients sick with the virus. These early policies limited economic activity and increased behavioral changes, such as reduced travel and social contact. More individuals began working from home or not working at all, lowering economic output. This resulted in many commodity-exporting countries to experience a sharp fall in prices of commodities (Hevia and Neumeyer 2020). Furthermore, a decline in consumer spending dominated in the short-run, indicating a potential price drop of consumer goods in response to COVID-19, perhaps leading to price changes in raw materials (Balleer et al. 2020). Balleer et al. (2020) conducted an analysis on the reported impact of COVID-19 on planned price changes. They surveyed 6,000 firms in the German economy, of whom approximately 80% reported adverse effects on business productivity in direct correlation with COVID-19. Additionally, they estimated an 11-percentage point increase in the probability of a price drop in response to COVID-19, as reported by firms in 2020 (Balleer et al. 2020).

Yet, the pandemic spurred a shift in preferences among individuals, leading to increased demand for dimensional lumber and pulpwood products (i.e., finished wood products) (van Kooten and Schmitz 2022). For example, there was increased demand to manufacture personal protective equipment for public health (Hilsenroth et al. 2021). Furthermore, according to Liu and Su (2021) the pandemic resulted in a shift in housing demand from city centers to suburbs and rural housing. They suggested with the rise of remote work that there was a diminished need for living close to offices and workspaces (Liu and Su 2021). Additionally, demand for packaging and shipping materials increased in response to online shopping and the need to create at-home offices (van Kooten and Schmitz 2022; Hilsenroth et al. 2021). Nevertheless, increased demand for finished wood products did not necessarily correspond with increased prices for standing timber.

The literature exploring COVID-19-related price effects on stumpage values have looked at price trends at varying points in time. For example, the pandemic led to an increase in the price of Southern softwood composite lumber, from $333 per thousand board feet (mbf) in April 2020 to $900 mbf in April 2021, a 170% increase from 2020-2021 (Fastmarkets RISI 2021). van Kooten and Schmitz (2022) and Prestemon and Guo (2022) explored impacts of COVID-19 on the forestry sector from 2020 to 2021. They attributed price changes partly to labor shortages that resulted from policies mandating citizens to stay home to prevent the spread of the virus and hesitancy to return to social settings. Labor shortages were also impacted by early retirement (Faria-e-Castro 2021) and limited immigration (U.S. Department of State 2020), in addition to COVID-19 illness.

On the other hand, according to Zhang and Stottlemyer (2021), average sawtimber prices were lower in 2020 as compared to the two previous years. For example, Southern softwood composite lumber was $476 mbf in April 2018 or 30% lower compared to 2020, and $402 mbf in April 2019 or 17% lower compared to 2020 (Fastmarkets RISI 2021). They argue that the combination of public health regulations and recommendations, such as social distancing, lockdowns, and quarantines, resulted in a slowdown of production activity for a period soon after COVID-19 became a concern (Hevia and Neumeyer 2020).

The U.S. South has approximately 245 million acres of forestland (1 acre = 0.405 ha), covering about 46% of the total land use. Of these, 87% are privately owned, including 147 million acres (60%) private non-corporate and 65 million acres (27%) private corporate (Oswalt et al. 2019). The South produces approximately 60% of the Nation's timber products, almost entirely from private forests, as well as produces a significant amount of wood products for the U.S. and global market, generating over $130 billion of gross output annually (Dahal et al. 2015).

In the early days of the COVID-19 pandemic, U.S. case-to-death ratio was relatively high compared to the later stages of the pandemic. For example, on May 3, 2020, there were approximately 200,000 documented U.S. COVID cases, with over 13,000 COVID-related deaths (6.5% mortality rate) (Johns Hopkins University and Medicine 2022). We compare this to a later wave in the pandemic, January 10, 2021, with a recorded 1.74 million cases and 23,000 COVID-related deaths (1.3% mortality rate)[1]. Even though the case count was relatively low across the Nation, including the U.S. South early in the pandemic (Figure 1 and Table 1), the high mortality rate and overwhelmed healthcare systems encouraged adoption of strict policies to prevent further spread of the virus.

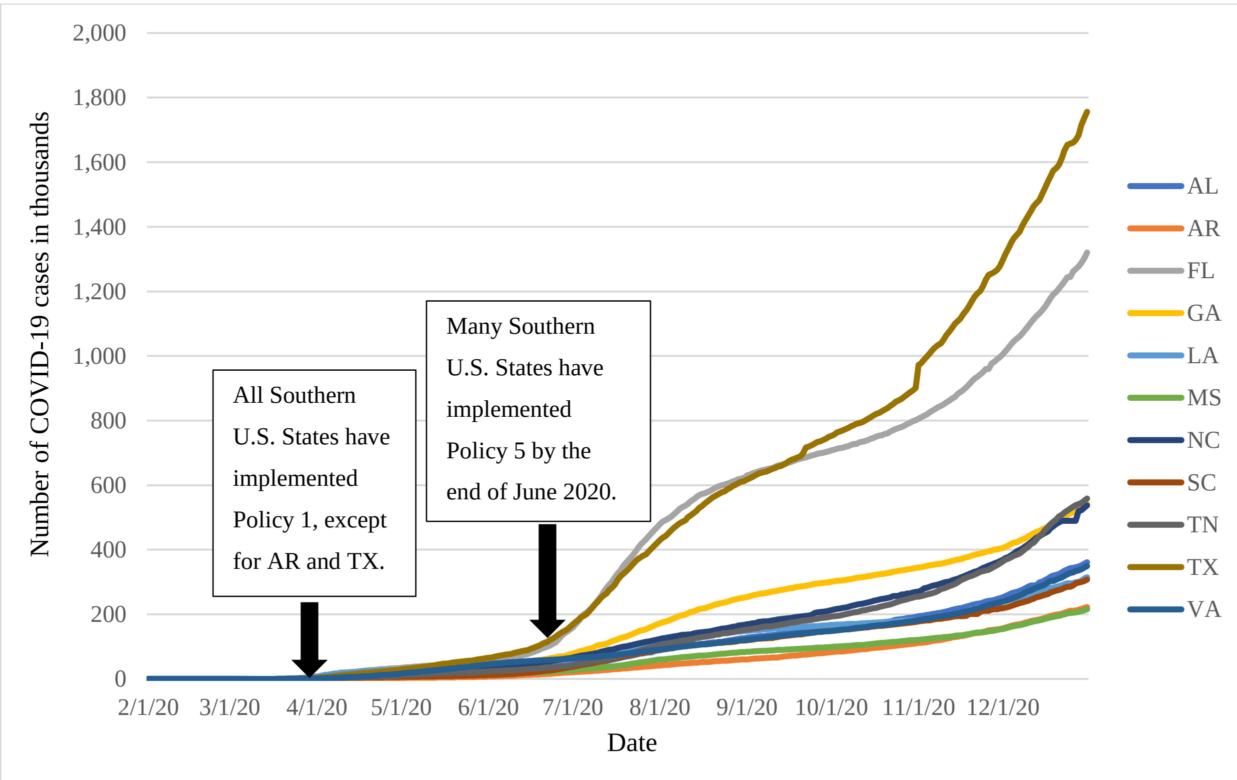

Figure 1. COVID-19 cases in the Southern U.S. from February 1, 2020, to December 31, 2020. Data via the Centers for Disease Control and Prevention (CDC 2021).

[1] Confounding factors, such as the availability of vaccines likely reduced the mortality rate later on in the pandemic. The purpose of this example is to describe why harsh lockdown policies were put in place even though case-counts were relatively low across the U.S. South, as compared to later waves of the pandemic when lockdown policies were not put in place.

Table 1. COVID-19 cases in each Southern U.S. State by month from March to June 2020. By June 2020, Mississippi had the highest amount of reported cases as a percent of total State population. Total State population is via the United States Census (census.gov).

State	Mar-20 cases	Percent of population	Apr-20 cases	Percent of population	May-20 cases	Percent of population	Jun-20 cases	Percent of population	Total state population (2022)
MS	6,814	0.23%	15,484	0.52%	27,247	0.92%	58,743	1.98%	2,961,279
AR	553	0.02%	3,101	0.10%	7,064	0.23%	20,053	0.67%	3,011,524
LA	5,213	0.11%	27,937	0.60%	39,815	0.85%	58,093	1.25%	4,657,757
AL	997	0.03%	7,063	0.14%	17,849	0.36%	38,045	0.76%	5,024,279
SC	1,083	0.02%	6,095	0.12%	11,859	0.23%	36,297	0.71%	5,118,425
TN	1,921	0.03%	10,653	0.15%	22,461	0.33%	41,756	0.60%	6,910,840
VA	1,247	0.01%	15,852	0.18%	44,600	0.52%	62,774	0.73%	8,631,393
NC	1,491	0.01%	10,012	0.10%	27,668	0.27%	64,665	0.62%	10,439,388
GA	3,927	0.04%	24,856	0.23%	43,369	0.40%	76,054	0.71%	10,711,908
FL	6,739	0.03%	33,683	0.16%	56,077	0.26%	152,277	0.71%	21,538,187
TX	3,266	0.01%	28,087	0.10%	64,287	0.22%	159,986	0.55%	29,145,505

Note: MS= Mississippi, AR= Arkansas, LA= Lousiana, AL= Alabama, SC= South Carolina, TN= Tennessee, VA= Virginia, NC= North Carolina, GA= Georgia, FL= Florida, TX= Texas

COVID-19-related policy decisions were largely left up to state and local governments. Policies varied over time and across counties and cities, reflecting changing and highly local perceptions of the COVID-19 caseload, the status of healthcare systems, and later on, emerging new variants and vaccination rates.

Since COVID-19 is relatively novel, there are only few studies to draw from that specifically use regression discontinuity design (RDD) or time regression discontinuity design (T-RD) methods to assess COVID-19-related commodity price impacts, and none that we are aware of that assess timber prices. Diop and Vedrine (2020) and Cuaresma and Heger (2019) use RDD methods to assess forestry-related policies in Africa, and Guan and Zhang (2022) use RDD methods to explore logging bans in China. Typically, RDD is used when there is a clear policy or spatial break (as compared to a time break). There are a few studies that we present here, which consider food-crop price changes, virus spread, and demand for healthcare using T-RD methods during COVID-19 (Ruan et al. 2021; Liu et al. 2021).

Studies that have assessed the causal effects of lockdown policies on COVID-19 spread and demand for new health services have focused primarily on different behavior changes in the health sector. Bakolis et al. (2021) investigated changes in daily mental health service use and mortality using T-RD methods, finding causal evidence that lockdown policies reduced inpatient admissions for mental health services compared to the pre-lockdown period. Similarly, Aiken et al. (2020) found that European countries, including Northern Ireland and Portugal, showed significant increase in self-managed telemedicine as compared to the pre-COVID period. Furthermore, Liu et al. (2021) evaluated COVID-19 policy effectiveness in controlling the spread of infection in China, Germany, Austria, and the United States using T-RD methods, and were one of the first to take into consideration the effect through time on behavioral response. They found that policies implemented later in the pandemic exerted a weaker effect on controlling COVID-19 case counts (Liu et al. 2021). For this article, we drew on the study design of Ruan et al. (2021), which used T-RD to causally assess changes in the level of Chinese cabbage prices in response to the lockdown policies in China. Ruan et al. (2021), did not explore the effects of varying policies over different regions in China, which we aim to address in this study.

This study, to our knowledge, is the first to explore roundwood prices in the southern U.S. in relation to various COVID-19 policies using causal analysis methods. Furthermore, other researchers have explored the effects of COVID-19 policies on prices of goods and behavior changes, but typically they have largely ignored how policies varied over space and through time (Ruan et al. 2021; Bakolis et al. 2021; Liu et al. 2021; Aiken et al. 2020). The purpose is to explore the causal effects of the COVID-19 lockdown on roundwood prices in the U.S. South using T-RD methods to assess timber price changes, as well as to explore price effects of varying COVID-19 policies across Southern counties using a fixed effect regression.

The rest of the article is organized as follows. Next we describe the methods used for analyses. The data was collected from publicly available sources, which we outline in the section after methods. Results from the T-RD estimation are then presented, followed by associated sensitivity analyses. We then describe the fixed effects estimation findings, which emphasize the different

COVID-19-related policies put in place across micromarkets. We conclude with a discussion of limitations and implications of model results.

METHODS

Detailed discussions of appropriate use of regression discontinuity design (RDD) as a method of causal inference have been published in Lee and Lemieux (2010) and Hahn, Todd, and Van der Klaauw (2001). Via Hahn, Todd, and Van der Klaauw (2001), the goal of the RDD method is to determine the effect of a binary treatment x_i on an outcome y_i. Each individual either receives or does not receive a treatment (observed by what is known as the "running variable"), and no individual is observed in both states at the same time (Hahn et al. 2001). Let y_{1i} denote the outcome with treatment and y_{0i} denote the absence of treatment. Additionally, let $x_i = 1$ if treatment is received and $x_i = 0$ if the treatment is not received. The model for the observed outcome can be written as:

$$y_i = \propto_i + x_i(\beta_i) \tag{1}$$

Where: $\propto_i \equiv y_{0i}$, and, $\beta_i \equiv y_{1i} - y_{0i}$.

There are two main types of RDD, the sharp and fuzzy design (Hahn et al. 2001). With the sharp design, treatment x_i is deterministic $[z_i, x_i = f(z_i)]$, where z_i takes on a continuum of values, and the point z_0, where the function $f(z)$ is discontinuous is assumed to be known. With fuzzy design, the conditional probability is known to be discontinuous at z_0 and the treatment assignment is not a deterministic function of z_i. We use a sharp time regression discontinuity design (T-RD), because there is a clear cutoff period, to identify the causal effects of lockdown policies on roundwood prices in the southern U.S.

Time Regression Discontinuity Design (T-RD) or Regression Discontinuity Design in Time (RDiT) is an effective method to assess causal policy impacts. From this point forward, we will refer to this method as T-RD. The main difference in interpretation between the standard RDD and T-RD is that the running variable is time itself (Hausman and Rapson 2018). Our cutoff point is based on the first date of known COVID-19 cases in the United States, beginning in March of 2020. Additionally, 100% of COVID-19 induced mandatory stay-at-home lockdowns in the southern states were imposed between April and June 2020. Other policy measures, such as advisory or recommendations to remain at home, were implemented only after March-April 2020. Therefore, we chose May-June as the time cutoff to allow for the lag between behavioral changes and COVID-19 policies in late March.

Similar to Calonico et al. (2014), Heckman and Vytlacil (2007), and Imbens and Wooldridge (2009), we adopt the potential-outcomes framework to identify causal effects of COVID-19 prevalence on timber product prices across the southern U.S. states. For each county i the scalar random variable Y_i denotes price of timber products. The scalar regressor X_i is the "running variable," which determines treatment assignment based on a known cutoff point $\bar{x}$, defined as the beginning of widespread COVID-19 policy prevalence in the Sothern United States, which we determine to be May-June 2020. Let $[\{Y_i(0), Y_i(1), X_i\}' : i = 1,2, \dots, n]$ be a random sample from the population $\{Y(0), Y(1), X\}'$, where Y(1), and Y(0) denote the potential timber prices with and without treatment. In our study, treatment is defined as a county in the southern U.S. being subject to a COVID-19 lockdown policy, which only occurs after spring 2020. Treatment assignment is determined when county i is assigned to the treatment condition (that is, if $X_i \geq \bar{x}$) and is assigned to the control condition if $X_i < \bar{x}$.

Therefore, the observed outcome is:

$$Y_i = \begin{cases} Y_i(0) & if\ X_i < \bar{x} \\ Y_i(1) & if\ X_i \geq \bar{x} \end{cases} \tag{2}$$

Thus, the T-RD design of the estimation strategy is:

$$\ln(Y_i) = \beta_0 + \beta_1 * 1(X_i \geq \bar{x}) + \phi * f(X_i) + \chi * 1(X_i \geq \bar{x}) * f(X_i) + \varepsilon_i \tag{3}$$

where $\ln(Y_i)$ is the natural logarithm of each of the roundwood prices in each county (i) in each bi-monthly time period (X_i). The dummy $1(X_i \geq \bar{x})$ equals one if time is post period 9 (May-June 2020) and zero if before period 9. Furthermore, $f(X_i)$ contains the polynomial time trend to flexibly control for time series variation in wood products prices, which would have occurred in the absence of the lockdown. The estimated effect of lockdown policies implemented at time $\bar{x}$ is represented by the estimated value of β_1. Equation (1) is estimated for each industrial roundwood product, including pine pulpwood, pine chip-n-saw, pine sawtimber, hardwood pulpwood, and hardwood sawtimber.

Additionally, with RD design, the direction of the slope of the data during the period before and after the cutoff period is typically constant. If there is a change in the slope at the cut-point, this is considered a Kink RD. The primary differences in Kink RD estimation are that the derivative of the regression function is set to one, and the kernel function is set to uniform (Calonico et al. 2014). The kernel function is used to construct the local-polynomial estimator.

Equation 3 assumes that all counties are impacted by the same type of lockdown policy in the same time period $\bar{x}$. However, each county was subject to multiple policies over time (see Figure 3 for a description of the alternative policy types through time during 2020). To examine the differential impacts of alternative policy effects, we estimate a series of fixed effects regressions for each roundwood type. We aggregated up from the county-level to micromarket averages across variables:

$$\ln(Y_i) = \mathrm{X}_{it}'\beta + \alpha_i + \varepsilon_{it} \;,\;\; \mathrm{i} = 1, \ldots, \mathrm{n},\; \mathrm{t} = 1, \ldots, \mathrm{T} \tag{4}$$

where $\ln(Y_i)$ is the natural logarithm of each of the roundwood prices in each micromarket (i) in each bi-monthly time period (X_i). The fixed effects approach takes α_i to be an unobserved group-specific constant term in the regression (Greene 2018), for example, we assume forest cover and economic activity from the forestry sector within micromarket county are fixed. Parameters we are most interested in exploring are the effects of different policies as a comparison of findings to the T-RD estimator.

Data

We created a time-varying panel dataset for all U.S. South counties included in the Forest2Market micromarket dataset (N=11,004 counties) (Forest2Market 2021). We first gathered Forest2Market bi-monthly micromarket price data. Micromarkets are broken into 39 regions across the South, encompassing eleven states, including: Alabama, Arkansas, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, Florida, and eastern Texas. Micromarket prices were matched to each county for twelve bi-monthly periods from 2019 to 2020 for T-RD estimation[2]. We then aggregated all variables up to the micromarket level by taking averages of co-variates for the fixed effects regressions to correct for autocorrelation between counties. We collected open-access data from the Centers for Disease Control and Prevention (CDC 2021), including COVID-19 policies and when they occurred and COVID-case counts by county. We characterized policies as follows according to the CDC labelling (See Table 2):

Table 2. Policy orders as described by the Centers for Disease Control and Prevention (CDC 2021). Policy 4 did not occur in any of the counties we observed in our dataset in the Southern United States.

Policy 0	No policy or order to stay home
Policy 1	Mandatory for all individuals
Policy 2	Mandatory only for all individuals in certain areas of the jurisdiction
Policy 3	Mandatory only for at-risk individuals in the jurisdiction
Policy 4	Mandatory only for at-risk individuals in certain areas of the jurisdiction
Policy 5	Advisory or recommendation to stay at home

Policy 1 occurred only in period 8, March-April (n=790 counties) and period 9, May-June (n=387 counties) 2020 in some counties across the U.S. South. Policy 1 occurred in 100% of counties in Alabama, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee and Virginia in Period 8. Policy 1 also occurred in period 9 in 100% of counties in Florida, Louisiana, North Carolina, South Carolina and Virginia. Yet, Policy 1 never occurred in Texas or Arkansas in either period, with counties that we can observe. Furthermore, multiple policies occurred within the same period. This is likely, because a policy lapsed and then was reinstated in the same bi-monthly time period, or a policy lapsed and a new policy was put in place. For example, 49% of counties had both Policy 1 and Policy 5 from March to April 2020. Georgia was the only state to put Policy 3 in place, which occurred in the same bi-monthly time period as Policy 1 for all periods. Policy 4 was never found in any county in the U.S. South but did occur in other States across the U.S.

[2] The dataset is broken into twelve price periods. January-February 2019 = Period 1, March-April 2019 = Period 2… November-December 2020 = Period 12.

Some scholars who have conducted analyses on COVID-19 policies have assumed a lag between policy implementation and societal behavioral changes (Liu et al. 2021). Others have conducted sensitivity analyses between COVID-19 policy implementation and changes in commodity prices (Ruan et al. 2021). We, therefore, checked price changes in period 8 and period 9. A similar causal effect can be observed in both period 8 and 9, however, some products have an outlier, where the price increased during period 8, and then sharply dropped during period 9 (Appendix A). In addition, our data source collects infrequent information (bi-monthly). We, therefore, chose to conduct analysis at period 9, which we believe better represents the effect of the COVID-19 policies and behavioral changes captured in the market.

Furthermore, to measure the differential impacts of each policy type on timber prices, we collected information about behavioral changes from COVID-19 policies, as well as other supply and demand determinants (Guerrieri 2022; Schemer et al. 2022; Cot et al. 2021). We collected an indicator of travel out of the home via Apple Inc., which took an aggregate, county level time varying measure of driving requests via Apple Maps[3]. Apple Inc. created a daily baseline of average number of travel requests prior to the Pandemic. They then tracked requests above and below baseline starting January 1, 2020. We aggregated this information to bi-monthly indicators of movement above and below baseline (Apple Inc.). We acknowledged this information might have measurement error. For example, an individual could request driving directions and not make the trip, or individuals may not need directions and make a trip without requesting directions. Furthermore, this data does not measure individuals who do not have an iPhone. However, we observed a sharp decrease in the number of map requests below baseline starting March 2020 and then an increase back to baseline by July 2020, reflecting the potential impacts of policy changes. Additionally, there were approximately 113.5 million iPhone users in the U.S. in 2020 (Ruby 2022), or approximately 34% of the total U.S. population, indicating the technology is widely used. Globally, researchers have used the Apple mobility data to explore COVID-19 impacts (Venter et al. 2020; Kurita et al. 2021; Nouvellet et al. 2021; Jing et al. 2021; Hu 2021). For example, Cot et al. (2021), were able to identify the period of social distancing via Apple mobility data independently of political decisions.

[3] Apple Inc. discontinued open access to mobility trends. You can view a press release announcing the data here: https://www.apple.com/newsroom/2020/04/apple-makes-mobility-data-available-to-aid-covid-19-efforts/

Moreover, we included the percentage of the county population with COVID-19. However, some measurement error exists within this variable. We obtained daily measurements of COVID-19 cases for each county from the CDC. Some counties miscounted number of cases, by reporting more cases than existed. The county would then reduce the number of cases at a later date to reflect the true number of COVID-19 cases in the population. This rough measurement is generally acceptable since we aggregated to bi-monthly periods (absorbing daily miscounts). Furthermore, we were only able to obtain a yearly county population number from the 2020 Census. Therefore, the county population is constant across bi-monthly COVID-19 case averages. However, there is likely not a significantly large death or migration rate at the county level. Again, we averaged county-level information to the micromarket level for FE regressions. Finally, we included average precipitation levels via the National Oceanic and Atmospheric Administration (NOAA 2022), to control for weather-related logging factors (Greene et al. 2004).

Summary statistics of micromarket-level data are presented in Table 3. The average price between 2019 and 2020 for pine sawtimber was $23/ton, pine pulpwood was $7/ton, and pine chip-n-saw was $14/ton. The advisory or recommendation policy was put in place for the longest number of days across bi-monthly periods (average of 18 days), followed by no policy (average of 14 days), lockdown policy (average of 4 days). The policies which dictate only certain individuals within a jurisdiction were only applied in Georgia (Policy 2 and Policy 3). Mandatory for at risk individuals in a jurisdiction was applied an average of 5 days within a bi-monthly period, and mandatory only for all individuals in certain areas of the jurisdiction was applied on average less than one day within a bi-monthly period.

The percent of the population with COVID-19 in 2020 was still relatively low, with an average of 0.01% of a county infected with the disease (from March-December 2020). Furthermore, to assess movement as a potential indicator of economic activity, we include mobility data collected by Apple Inc., which calculated a baseline level of Apple Map requests (baseline = 100). An indicator above 100 is above-average map requests. The average number of map requests was above baseline (about 118), with a minimum of 74 and a maximum of 257. Below-average map requests occur most often right after the lockdown policies were implemented. Additionally, we include the average precipitation by county (average of 10 inches).

*Table 3. Summary statistics wit*h aggregated averages to *the micromarket level.*

Variable Name	Unit	Mean	Std. dev.	Min	Max	Unit	mean	Std. dev.	Min	Max
Hardwood pulpwood	natural log price per ton	2.04	0.50	0.68	3.07	price per ton	7.71	1.64	1.98	21.63
Pine sawtimber	natural log price per ton	3.15	0.21	2.33	3.60	price per ton	23.25	1.24	10.31	36.64
Pine pulpwood	natural log price per ton	2.01	0.44	0.71	3.08	price per ton	7.49	1.55	2.04	21.82
Pine chip-n-saw	natural log price per ton	2.68	0.24	1.95	3.29	price per ton	14.52	1.27	7.03	26.80
Hardwood sawtimber	natural log price per ton	3.55	0.17	3.05	4.03	price per ton	34.68	1.19	21.02	56.27
No policy	policy days post-period 6	15.77	21.66	0.00	62.00					
Mandatory for all (lockdown)	policy days post-period 6	3.88	9.25	0.00	39.00					
Mandatory only for all individuals in certain areas of the jurisdiction	policy days post-period 6	0.01	0.19	0.00	3.21					
Mandatory only for at-risk individuals in the jurisdiction	policy days post-period 6	5.22	14.81	0.00	62.00					
Advisory or recommendation	policy days post-period 6	18.83	24.49	0.00	62.00					
Percent of population with COVID-19	percent of micromarket population test positive for COVID-19	0.01	0.01	0.00	0.05					
Precipitation	average micromarket average precipitation by bi-monthly period	9.94	3.32	2.25	21.98					
Apple Inc. Mobility	request for apple maps above or below baseline level of requests	118.22	31.92	74.84	257.66					
Periods (1-12)	bi-monthly period	6.50	3.46	1.00	12.00					

Observations (N) = 468

Observations post-period 6 (after COVID-19 policies) (n) = 263

RESULTS

Figure 2 and 3 present graphical analyses of the different roundwood products. Figure 3 depicts the discontinuous jump in period 9 of mean prices for each timber product type in the southern U.S. We carefully observed the slope of mean price before and after the cutoff period. We can clearly see that hardwood sawtimber, hardwood pulpwood, and pine pulpwood could be categorized as a Kink RD, while pine sawtimber and pine chip-n-saw have a typical RD design.

Figure 2. Mean prices of roundwood products in the U.S. South with cutoff at period 9 (May-June 2020).

Figure 2 assesses the fit of the regression function. Using rdplot in STATA (Calonico et al. 2015), a command that implements different bins to approximate the underlying regression function (IMSE-optimal selectors), we detect a discontinuity at the cutoff through the visual representation of the mean variability of the price data for each product type (Calonico et al. 2015). The most common RD plot is an evenly-spaced binning of the data (Calonico et al. 2015). Table 4 presents the IMSE optimal evenly spaced bin lengths and observations to the left and right of the cutoff.

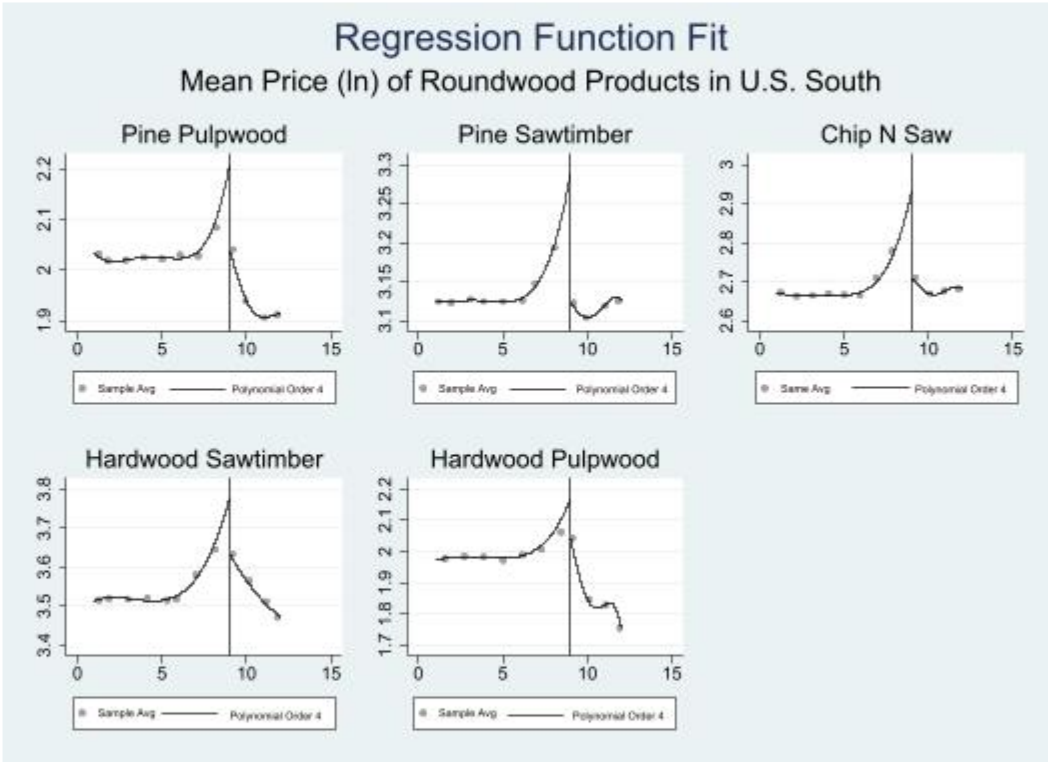

Figure 3. rdplot using IMSE optimal evenly spaced bins. All plots show a discontinuous cutoff at period 9 (May-June 2020), indicating a decrease in price caused by COVID-19 policy implementation.

Table 4. rdplot using IMSE optimal evenly spaced bins, average bin length and IMSE optimal bins, observations left of the cutoff N = 7336, and right of the cutoff N = 3668.

4th order polynomial fit	Left of cutoff	Right of cutoff
Pine pulpwood		
Average bin length	0.5333	0.375
IMSE optimal bins	15	8
Pine sawtimber		
Average bin length	0.381	0.375
IMSE optimal bins	21	8
Pine chip-n-saw		
Average bin length	0.471	0.429
IMSE optimal bins	17	7
Hardwood sawtimber		
Average bin length	0.571	0.333
IMSE optimal bins	14	9
Hardwood pulpwood		
Average bin length	1.143	0.2
IMSE optimal bins	7	15

Using the rdrobust command in STATA 17.0 (Calonico et al. 2017), Table 5 and Table 6 present the T-RD estimates for the effect of COVID-19 stay-at-home policies on the price of different roundwood products in the U.S. South. Rho is the bias bandwidth used to construct the bias correlation estimator divided by the main bandwidth used to construct the RD point estimator. We present three different procedures:

1. Conventional T-RD estimates with a conventional variance estimator as proposed by Calonico et al. (2014),
2. Bias Corrected T-RD with a conventional variance estimator as proposed by Imbens and Kalyanaraman (2012), and
3. Bias Corrected T-RD with a robust variance estimator as proposed by Ludwig and Miller (2007). These estimators are all consistent and asymptotically efficient as sample size increases (Calonico et al. 2014).

Table 5 presents the Kink T-RD estimates for pine pulpwood, hardwood sawtimber, and hardwood pulpwood. The Kink T-RD estimates are statistically significant for all product types ($p < 0.01$). We find under the conventional scenario pine pulpwood price dropped by approximately 26% after policy implementation, hardwood sawtimber dropped by around 14% after policy implementation, and hardwood pulpwood dropped by approximately 30% after policy implementation.

Table 5. Sharp kink T-RD using MSE optimal bandwidths. Number of observations left of cutoff N= 7336. Number of Observations right of cutoff N = 3668, for all regressions presented in this table.

Sharp Kink Time Regression Discontinuity (T-RD) using MSE optimal bandwidth selector with Uniform Kernel

Pine pulpwood	**Left of cutoff**	**Right of cutoff**
Effective number of obs.	2751	3668
Rho	0.612	0.612
	Coefficient	**Standard error**
Conventional	-0.2634***	(0.0678)
Bias corrected	-0.3126***	(0.0678)
Robust	-0.3126***	(0.0905)
Hardwood sawtimber	**Left of cutoff**	**Right of cutoff**
Effective Number of Obs.	2751	3668
Rho	0.538	0.538
	Coefficient	**Standard error**
Conventional	-0.1409***	(0.0263)
Bias corrected	-0.1647***	(0.0263)
Robust	-0.1647***	(0.0337)
Hardwood pulpwood	**Left of cutoff**	**Right of cutoff**
Effective number of obs.	2751	3668
Rho	0.621	0.621
	Coefficient	**Standard error**
Conventional	-0.2953***	(0.0863)
Bias corrected	-0.4885***	(0.0863)
Robust	-0.4885***	(0.1360)

*** p<0.1, ** p<0.05, ***p<0.01**

Table 6 presents the T-RD estimates for pine chip-n-saw and pine sawtimber. Again, we find estimates to be statistically significant ($p < 0.001$). Under the conventional scenario pine chip-n-saw price drops by 6.8% after policy implementation, and pine sawtimber price dropped by 12% after policy implementation.

Table 6. Sharp T-RD using MSE optimal bandwidths. Number of Observations left of cutoff N= 7336. Number of observations right of cutoff N = 3668, for all regressions presented in this table.

Sharp Time Regression Discontinuity (T-RD) using MSE optimal bandwidth selector with Triangular Kernel

Pine chip-n-saw	**Left of cutoff**	**Right of cutoff**
Effective number of obs.	917	1834
Rho	0.435	0.435
	Coefficient	**Standard error**
Conventional	-0.0680***	(0.0098)
Bias corrected	-0.0519***	(0.0098)
Robust	-0.0519***	(0.0091)
Pine sawtimber	**Left of cutoff**	**Right of cutoff**
Effective number of obs.	1834	2751
Rho	0.48	0.48
	Coefficient	**Standard error**
Conventional	-0.1179***	(0.0168)
Bias corrected	-0.1401***	(0.0168)
Robust	-0.1401***	(0.0235)

*** p<0.1, ** p<0.05, ***p<0.01**

Sensitivity analyses of T-RD results

The benefit of RDD is that it can proxy for a randomized experiment when it is not possible to randomly assign individuals to a treatment group (Lee and Lemieux 2010). Yet, there are four assumptions when using the T-RD method. The first assumption of using T-RD is that the only reason for price discontinuity during COVID-policy implementation is the policies themselves (Ruan et al. 2021). It is possible that some other confounding factors may impact timber prices at the same time as COVID-policy implementation. Nevertheless, any price changes near the lockdown date will be absorbed by the flexible polynomial time trend and will not contribute to the bias (Ruan et al. 2021). Ruan et al. (2021) conducted a sensitivity analysis by shifting the cut-off date to evaluate if there was a significant price effect before the COVID-19 policy implementation. We conducted a similar test, using period 7 (January-February 2020) as the test cut-period using MSE optimal bandwidths. We chose this as the test period because it is before any COVID-19 policies are put in place but is still within proximity to the treatment period. We found no statistical significance for pine pulpwood and hardwood sawtimber prices with discontinuity at period 7. We found a statistically significant effect for pine chip-n-saw, pine sawtimber, and pine pulpwood, but the sign of their coefficients is opposite from the estimates after COVID-19 policy implementation. To be clear, we would expect a price decrease visually inspecting Figures 4 and 5. Yet, the sensitivity analysis results in positive coefficients, indicating some other factors driving the prices during this period. Detailed results are presented in Appendix B.

Second, while this is quite unlikely (Ruan et al. 2021), the identification assumption of T-RD is violated if there is self-selection at the cut-off (Hausman and Rapson 2018). Those counties which implemented a lockdown most likely did not consider implications, or made the choice to implement a COVID-19 policy, as they related to underlying factors that also influenced timber markets. Third, time series data can show serial correlation or serial dependence, when prices are nonrandom and correlated to their prior values. High-frequency data allows for more power but may be more likely to suffer from autoregression (Hausman and Rapson 2018). Hausman and Rapson (2018) suggest adding a lagged dependent variable in estimation, especially when the policy window is longer. Meaning, if the study included only the day immediately before and after the policy change that would be a short-run effect. In our case bi-monthly periods, a longer window may be more likely to experience autoregression. We, therefore, estimate the T-RD by adding the lagged dependent variable (Appendix C), with no significant change in statistical significance.

Fourth, the choice of the time window is important. The use of observations far from the threshold is a “conceptual departure” from the identifying assumptions and can lead to a bias from unobservable confounders (Ruan et al. 2021). We present the most common regression discontinuity design using local polynomial estimation and inference with a mean square error (MSE) optimal bandwidth (Calonico et al. 2020). Yet, to test for other bandwidth choices, we present the coverage error robust (CER) optimal bandwidths (Calonico et al. 2020) and two MSE optimal bandwidth selector choices in Appendix D. The goal of the CER optimal estimator is to construct robust bias-corrected confidence intervals, which is optimal for inference. According to Calonico et al. (2020), MSE optimal and CER optimal procedures are complementary. The CER optimal bandwidths serve a fundamentally different goal than minimizing the MSE of the point estimator. In other words, the robust bias-corrected confidence intervals of the CE estimator have the smallest possible coverage error, or when the population of interest does not coincide with the population actually sampled (Calonico et al. 2020). The estimates are robust for all product types using CER optimal bandwidths ($p < 0.001$). Furthermore, we present two different MSE optimal bandwidth selectors for below and above the cutoff for the RD treatment effect estimator (Appendix D).

Fixed effects regression results

Using a FE regression, we explore the effect of various COVID-19 policies and other co-variates, which may have impacted roundwood prices. The Durbin-Wu-Hausman test (Hausman specification test) is used to assess the efficiency of the fixed effects estimator (compared to random effects). We found that the difference in coefficients is not systematic and can reject the random effects as inconsistent, thus opting for the fixed effects estimation. Econometric results for the fixed effects regression can be found in Table 7. There were N=468 micromarket observations, via 39 time-variant groupings with 12 observations per group (the bi-monthly periods).

Table 7. Fixed effects results with policy change count variables.

	1	2	3	4	5
	Pine Sawtimber (ln)	**Pine Pulpwood (ln)**	**Pine Chip-n-saw (ln)**	**Hardwood Sawtimber (ln)**	**Hardwood Pulpwood (ln)**
Pine Sawtimber (ln)		0.524***	0.249***	-0.116	0.246
		(0.10)	(0.07)	(0.09)	(0.18)
Pine Pulpwood (ln)	0.137***		0.053	0.088*	0.285**
	(0.04)		(0.05)	(0.04)	(0.11)
Pine Chip-n-saw (ln)	0.142***	0.115		-0.02	0.318**
	(0.04)	(0.11)		(0.06)	(0.14)
Hardwood Pulpwood (ln)	0.037	0.165*	0.085**	0.070**	
	(0.02)	(0.07)	(0.03)	(0.03)	
Hardwood Sawtimber (ln)	-0.069	0.199*	-0.021		0.275**
	(0.05)	(0.11)	(0.06)		(0.10)
No Policy	-0.001	-0.002*	0.00	-0.001	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mandatory for all (lockdown)	-0.002	-0.007***	0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Mandatory only for all individuals in certain areas of the jurisdiction	0.004	-0.056***	0.009	0.040***	0.029
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Mandatory only for at-risk individuals in the jurisdiction	-0.001	-0.002	0.001	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Advisory or recommendation	-0.001	-0.002*	0.001	-0.002*	-0.003
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Percent of Population with COVID-19	1.571	-1.493	-0.993	0.667	1.611
	-1.35	-2.11	-1.48	-1.33	-3.09
Precipitation	0.00	-0.002	0.002	0.002	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Apple Inc. Mobility	0.001	0.00	0.001	0.001	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Period=2 (Mar-Apr 2019)	-0.012	-0.060***	-0.002	-0.006	0.081***

	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)
Period=3 (May-Jun 2019)	-0.02	-0.087***	-0.021	0.033	0.092**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)
Period=4 (Jul-Aug 2019)	-0.027	-0.073***	-0.013	0.04*	0.083**
	(0.01)	(0.03)	(0.02)	(0.02)	(0.04)
Period=5 (Sep-Oct 2019)	-0.01	-0.087***	0.003	0.075***	0.108***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)
Period = 6 (Nov-Dec 2019)	-0.01	-0.081***	-0.005	0.072***	0.075*
	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)
Period=7 (Jan-Feb 2020)	0.012	-0.078**	0.023	0.090***	0.08*
	(0.02)	(0.03)	(0.03)	(0.03)	(0.05)
Period=8 (Mar-Apr 2020)	0.108**	0.156**	0.029	0.198***	0.217**
	(0.05)	(0.08)	(0.05)	(0.06)	(0.11)
Period=9 (May-Jun 2020)	-0.001	0.09*	-0.038	0.143***	0.257**
	(0.03)	(0.05)	(0.04)	(0.04)	(0.11)
Period=10 (Jul-Aug 2020)	-0.043	0.035	-0.051*	0.057	0.129
	(0.03)	(0.05)	(0.03)	(0.04)	(0.10)
Period=11 (Sep-Oct 2020)	0	-0.016	-0.044	0.017	0.102
	(0.03)	(0.05)	(0.03)	(0.03)	(0.08)
constant	2.585***	-0.869*	1.603***	3.471***	-1.154*
	(0.22)	(0.51)	(0.30)	(0.29)	(0.68)
R-sqr (Within/ Between/ Overall)	(0.28/ 0.55/ 0.52)	(0.40/ 0.27/ 0.28)	(0.24/ 0.55/ 0.48)	(0.38/ 0.05/ 0.04)	(0.43/ 0.04/ 0.09)
F-Statistic (Prob > F)	22.71***	503.51***	37.77***	127.38***	672.13***
*** p<0.1, ** p<0.05, ***p<0.01**					
Observations	468				
Number of Groups	39				
Observations per Group	12				

Results in Table 7 suggest that some COVID-19 policies had a decreasing price effect on standing timber markets in the U.S. South. An additional day of Policy 1 decreased price of pine pulpwood by 0.7%. Furthermore, Policy 2 decreased price of pine pulpwood by 5.6% yet had an increased price effect on hardwood sawtimber by 4%. Additionally, we found that percent of the population with COVID-19 and Apple Inc. mobility counts were not statistically significant. This could be because we aggregated the variation of these indicators to the micromarket level to account for autocorrelation across counties in this analysis.

DISCUSSION AND CONCLUSIONS

This study is the first to estimate the effects of COVID-19 policies on roundwood prices in the U.S. South using causal methods and the first to explore differential impacts of various COVID-19 policies on roundwood prices, not just COVID-19 lockdowns. By observing causal impacts of COVID-19 related policies we can potentially expect timber price fluctuations when future market shocks occur from state-level policies or recommendations. Using the T-RD methodology, we found that average prices for all wood products across the U.S. South significantly decreased ($p < 0.01$) soon after COVID-19-related policies were put in place by between 7% (for pine chip-n-saw) and 30% (for pine pulpwood). Pine sawtimber price dropped by an estimated 12% after Policy 1 implementation. Furthermore, using FE regressions, we observed the differential impacts of each COVID-19 policy. We found that additional days of Policy 1 resulted in a decrease in price for pine pulpwood, and Policy 2 resulted in a decrease in price of pine pulpwood and an increase in price for hardwood sawtimber. Lockdown policies (Policy 1) were in place for an average of four days across micromarkets. We may expect the price of pine pulpwood to drop by about 3% for a four-day lockdown. The respective methodological differences can explain the price variation. T-RD estimates are more robust at defining effects before and after the cutoff period. T-RD methods bin observations before and after the cutoff, and all observations are lumped into the “lockdown” category. Thus, the FE results estimate the effects of individual policies.

Typically, we may assume that if consumer demand for wood products increases, roundwood prices may follow suit. However, this was not the case during the COVID-19 policy period. We explore a few potential reasons. In general, a possible reason for roundwood price declines was a short-term reduction in production capacity by sawmills. In other words, a demand reduction. Gagnon et al. (2022) found that production declines of wood pellets in Canada directly resulted from sawmill closures. Rayonier Advanced Materials Inc. announced ceased or reduced operations on softwood sawmills in Canada starting early April 2020 (SeekingAlpha 2021), and Weyerhaeuser announced reduced operating capacity by 20% for lumber and 25% for engineered wood products on March 30, 2020 (International Forest Industries 2020). Additionally, worker illnesses were up in 2020 as compared to 2019, approximately 16% in the wood products sector and 42% in the paper products sector, resulting in a shrinkage of the workforce (about 3% lower from April to March 2020 as compared to those same months in the prior year) (Prestemon and Guo 2022). The worker illness increases may imply that mills were often unable to return to higher levels of production in response to strong product demand, even after lockdown policies were lifted. Additionally, mills did not demand much more wood (Prestemon and Guo 2022), perhaps due to production constraints and a limited workforce. Even though mills and big box stores were experiencing higher sales revenues (Prestemon and Guo 2022), loggers and landowners generally did not receive higher prices on their timber sales (Hilsenroth et al. 2021).

Furthermore, there may have been an initial demand decrease for wood-products across the market due to consumer uncertainty. Our results exploring the forest sector align with Del Rio-Chanona et al. (2020), who posited whether demand reductions early in the pandemic were postponed expenses or permanent. We observe that pine chip-n-saw recovered to above-average prices, compared to 2019, within one period after COVID-19 policies were implemented. Similarly, pine sawtimber recovered to the 2019 average price, within one period after COVID-19 policies were enforced. Pine pulpwood prices remained low and did not recover to pre-pandemic prices through December 2020.

Additionally, we found that when partial policies occurred for certain jurisdictions, prices were more variable (both an increasing and decreasing price effect for different roundwood products). On average, policy 2 lasted for less than one day. Yet, this may indicate that when harvest locations are uncertain, there may be a slight decline in supply. For example, a private landowner who adheres to the policy may choose to decline face-to-face contact (Mheidly 2020), with forest technicians and logging professionals while the policy is in place. Further research is warranted to robustly identify the potential reasons for differing price impacts when Policy 2 was implemented.

We acknowledge some limitations to our study. Foremost, other impacts such as inflation impacts on increased fuel costs (Coibion 2020), the Ukraine war (Shahini 2022), oligopsony power with timber consumers (Kanieski da Silva 2019), shifts from urban to suburban/ rural housing demand pressures (Liu and Su 2021), and other factors may have impacted timber products prices, especially as we move further away from the point in which policies were put in place. COVID-19 policies may have been an immediate shock to the market (Prestemon and Guo 2022). As we move farther away from policy implementation, the causal effect of COVID-19 on the timber markets becomes more ambiguous and mixed with other potential market drivers.

Furthermore, we observed a sharp increase in average prices of all roundwood products from January-February 2020 (about $1.00 above the previous year's average prices), just before COVID-19 policies were put in place. At this point, we can only speculate the reason for this price increase and would encourage an exploratory study to search for causal drivers. Moreover, we acknowledge our dataset is limited by bi-monthly prices, which averages out short-term (weekly or monthly) volatility. However, this is the best data available, and we are still able to observe a robust causal effect of COVID-19 policies on roundwood prices. Furthermore, we assessed the impacts on roundwood prices in the Southern region of the U.S. and suggest that a similar study in other regions, such as the Pacific Northwest, may be useful to assess COVID-19 policy effects on forestry products.

Lastly, wood products manufacturing and transportation were deemed "essential services" on March 19, 2020 (U.S. Department of Homeland Security 2020). However, many policies were implemented as early as March 15, 2020. This means that industries completely shut down for almost one business week, and then had to resume operations. This may have led to price changes simultaneous with policy changes, which may not be congruent with future policy implementation (if a policy were to be reinstated, wood products manufacturing and transportation might be immediately deemed essential). Therefore, these estimates may not fully reflect the causal effects of future policy changes.

In summary, our findings align with Prestemon and Guo (2022), which reported a sharp drop in the Nation's aggregate economic output in the second quarter of 2020. Demand for wood products resumed as residential homeowners shifted demand preferences, resulting in a relatively quick revival of roundwood prices (Prestemon and Guo 2022). As we recover from the COVID-19 pandemic and COVID-related policies end, we believe these findings may assist in decision-making or set expectations for future market disturbances in which new policies may significantly impact roundwood prices. For example, natural disasters such as wildfires and hurricanes are increasing in frequency and can reduce standing timber for a period of time soon after the shock (once salvage efforts have been exhausted) (Henderson 2022). Therefore, we may expect to see the opposite impact (price increase) on roundwood prices, particularly if there is an increase in consumer demand after a natural disaster event in tandem with unforeseeable policy changes.

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CONFLICT OF INTERESTS

The authors declare no conflict of interest.

DISCLAIMER

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APPENDIX A.

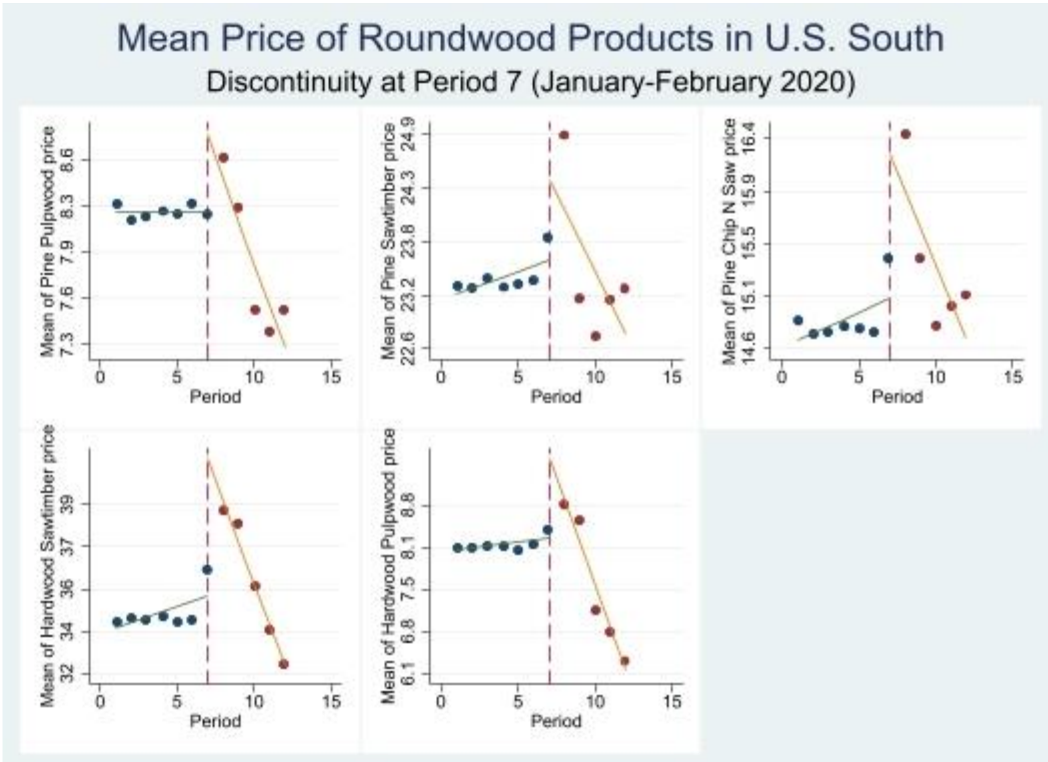

Figure 1A. We find no statistical significance for pine pulpwood and hardwood sawtimber price with discontinuity at period 7. We do find statistical significance for pine chip-n-saw, pine sawtimber, and pine pulpwood. However, the price at the discontinuous jump is increasing, indicating another factor (i.e., not pandemic polices) in the market may be having an effect in this period.

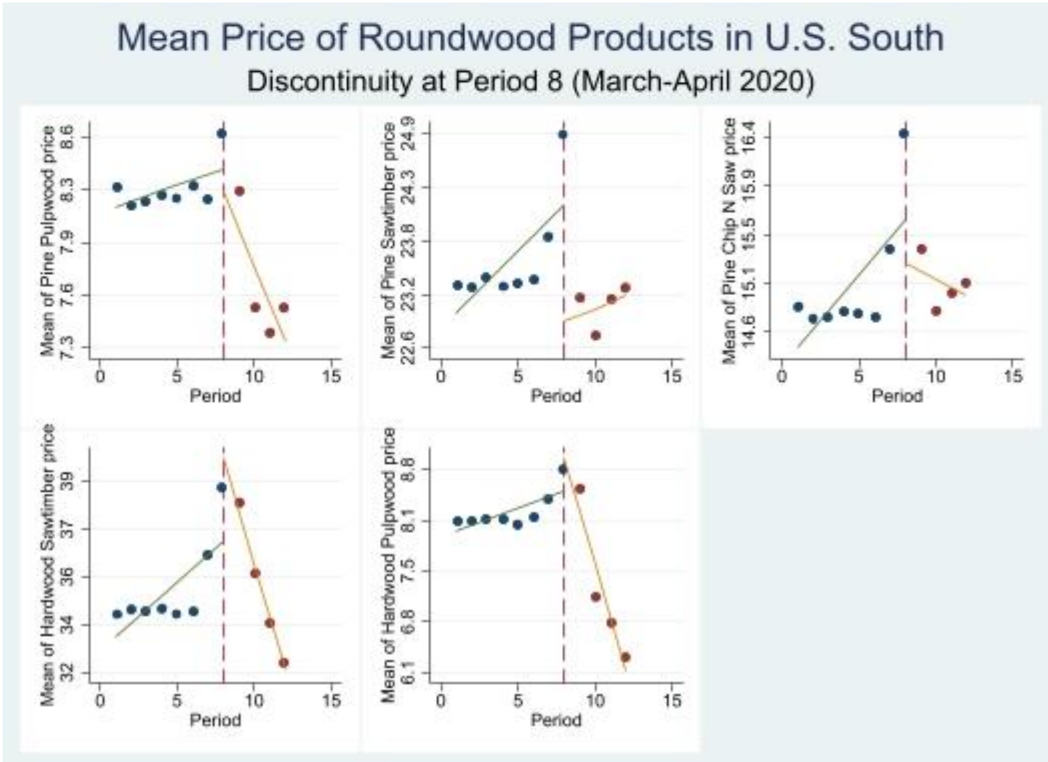

Figure 2A. We present roundwood price plots at period 8 (March-April 2020), when policies were first implemented in the southern U.S. We find a similar effect in period 9, where prices for average price of pine pulpwood, pine sawtimber, and pine chip-n-saw all decrease after policies are implemented. We do see a price increase in this time period for average hardwood sawtimber and pine pulpwood price. This may not be due to COVID-19 related policies, because it factors in prices before policies were implemented (beginning of March 2020).

APPENDIX B

Table 1B. Sensitivity analysis with running variable cutoff at period 7 (January-February 2020). Pine pulpwood price and hardwood sawtimber price are not statistically significant at this cut point. Pine chip-n-saw, pine sawtimber, and hardwood pulpwood are statistically significant, but the sign of the coefficient is opposite of what we would expect to see after COVID-19 policy implementation.

Sensitivity Analysis: Sharp Time Regression Discontinuity (T-RD) using MSE optimal bandwidth selector (Cutoff Period 7, Jan-Feb 2020) with Triangular Kernel

Pine pulpwood		**Left of Cutoff**	**Right of Cutoff**
	MSE Optimal Number of Obs.	5502	5502
	Effective Number of Obs.	1834	2751
	Rho	0.754	0.754
		Coefficient	**Standard Error**
	Conventional	-0.0046	(0.0336)
	Bias Corrected	-0.0039	(0.0336)
	Robust	-0.0039	(0.0232)
Pine chip-n-saw		**Left of Cutoff**	**Right of Cutoff**
	MSE Optimal Number of Obs.	5502	5502
	Effective Number of Obs.	917	1834
	Rho	0.582	0.582
		Coefficient	**Standard Error**
	Conventional	0.0457***	(0.0102)
	Bias Corrected	0.0462***	(0.0102)
	Robust	0.0462***	(0.0124)
Pine sawtimber		**Left of Cutoff**	**Right of Cutoff**
	MSE Optimal Number of Obs.	5502	5502
	Effective Number of Obs.	917	1834
	Rho	0.602	0.602
		Coefficient	**Standard Error**
	Conventional	0.0216**	(0.0104)
	Bias Corrected	0.0211**	(0.0104)
	Robust	0.0211*	(0.0125)

Hardwood sawtimber	**Left of Cutoff**	**Right of Cutoff**
MSE Optimal Number of Obs.	5502	5502
Effective Number of Obs.	1834	2751
Rho	0.858	0.858
	Coefficient	**Standard Error**
Conventional	0.0072	(0.0394)
Bias Corrected	0.0124	(0.0394)
Robust	0.0124	(0.0279)
Hardwood pulpwood	**Left of Cutoff**	**Right of Cutoff**
MSE Optimal Number of Obs.	5502	5502
Effective Number of Obs.	917	1834
Rho	0.673	0.673
	Coefficient	**Standard Error**
Conventional	0.0633***	(0.0077)
Bias Corrected	0.0625***	(0.0077)
Robust	0.0625***	(0.0094)

*** p<0.1, ** p<0.05, ***p<0.01**

APPENDIX C

Table 1C. Sensitivity analysis with lag dependent variable, using kink T-RD with MSE optimal bandwidths. The number of observations left of the cutoff is n=7335 and right of the cutoff is n= 3668. All coefficients are negative and statistically significant, matching the findings without using the lag dependent variable.

Sharp Kink Time Regression Discontinuity (T-RD), MSE Optimal, With Lag Dependent Variable with Uniform Kernel

Pine pulpwood		**Left of Cutoff**	**Right of Cutoff**
	Effective Number of Obs.	3668	3668
	Rho	0.615	0.615
		Coefficient	**Standard Error**
	Conventional	-0.1996***	(0.0397)
	Bias Corrected	-0.2630***	(0.0397)
	Robust	-0.2630***	(0.0763)
Hardwood sawtimber		**Left of Cutoff**	**Right of Cutoff**
	Effective Number of Obs.	2751	3668
	Rho	0.538	0.538
		Coefficient	**Standard Error**
	Conventional	-0.1405***	(0.0263)
	Bias Corrected	-0.1642***	(0.0263)
	Robust	-0.1642***	(0.0337)
Hardwood pulpwood		**Left of Cutoff**	**Right of Cutoff**
	Effective Number of Obs.	2751	3668
	Rho	0.621	0.621
		Coefficient	**Standard Error**
	Conventional	-0.2967***	(0.0863)
	Bias Corrected	-0.4898***	(0.0863)
	Robust	-0.4898***	(0.1360)

*** p<0.1, ** p<0.05, ***p<0.01**

Table 2C. Sensitivity analysis with lag-dependent variable, using T-RD with MSE optimal bandwidths. The number of observations left of the cutoff is n=7335, and right of the cutoff is n= 3668. All coefficients are negative and statistically significant, matching the findings without using the lag-dependent variable.

Sharp Time Regression Discontinuity (T-RD) MSE Optimal, With Lag Dependent Variable with Triangular Kernel

Pine chip-n-saw	**Left of Cutoff**	**Right of Cutoff**
Effective Number of Obs.	917	1834
Rho	0.437	0.437
	Coefficient	**Standard Error**
Conventional	-0.0677***	(0.0098)
Bias Corrected	-0.0517***	(0.0098)
Robust	-0.0517***	(0.0091)
Pine sawtimber	**Left of Cutoff**	**Right of Cutoff**
Effective Number of Obs.	1834	2751
Rho	0.481	0.481
	Coefficient	**Standard Error**
Conventional	-0.1173***	(0.0168)
Bias Corrected	-0.1393***	(0.0168)
Robust	-0.1393***	(0.0235)

*** p<0.1, ** p<0.05, ***p<0.01**

APPENDIX D

Table 1D. Sensitivity analysis using CER optimal bandwidths and MSE optimal bandwidths for below and above cut period 9 (May-June 2020) using kink T-RD. The number of observations for both analyses is n=7336 left of the cutoff and n=3668 right of the cutoff. The statistical significance is not changed, however, the coefficients change slightly from the MSE optimal with one optimal bandwidth selector for both above and below the cut period.

Sharp Kink Time Regression Discontinuity (T-RD) using CER optimal bandwidth selector with Uniform Kernel			**Sharp Kink Time Regression Discontinuity (T-RD) with two MSE optimal bandwidth selectors below and above the cutoff with Uniform Kernel**		
Pine pulpwood	**Left of Cutoff**	**Right of Cutoff**	**Pine Pulpwood**	**Left of Cutoff**	**Right of Cutoff**
Effective Number of Obs.	1834	2751	Effective Number of Obs.	917	3668
Rho	0.36	0.36	Rho	0.436	1
	Coefficient	**Standard Error**		**Coefficient**	**Standard Error**
Conventional	-0.1344***	(0.0331)	Conventional	-0.12175***	(0.0211)
Bias Corrected	-0.1437***	(0.0331)	Bias Corrected	-0.14369***	(0 .0211)
Robust	-0.1437***	(0.0506)	Robust	-0.14369***	(0.0506)
Hardwood sawtimber	**Left of Cutoff**	**Right of Cutoff**	**Hardwood Sawtimber**	**Left of Cutoff**	**Right of Cutoff**
Effective Number of Obs.	1834	2751	Effective Number of Obs.	917	3668
Rho	0.316	0.316	Rho	0.373	1
	Coefficient	**Standard Error**		**Coefficient**	**Standard Error**
Conventional	-0.0751***	(0.0110)	Conventional	-0.0739***	(0.0070)
Bias Corrected	-0.0760***	(0.0110)	Bias Corrected	-0.0760***	(0.0070)
Robust	-0.0760***	(0.0163)	Robust	-0.0760***	(0.0163)
Hardwood pulpwood	**Left of Cutoff**	**Right of Cutoff**	**Hardwood Pulpwood**	**Left of Cutoff**	**Right of Cutoff**
Effective Number of Obs.	917	1834	Effective Number of Obs.	1834	3668
Rho	0.365	0.365	Rho	0.431	1
	Coefficient	**Standard Error**		**Coefficient**	**Standard Error**
Conventional	-0.1967***	(0.0229)	Conventional	-0.1812***	(0.0239)
Bias Corrected	-0.1580***	(0.0229)	Bias Corrected	-0.3631***	(0.0239)
Robust	-0.1580***	(0.0172)	Robust	-0.3631***	(0.0619)

**** p<0.1, ** p<0.05, ***p<0.01***

Table 2D. Sensitivity analysis using CER optimal bandwidths and MSE optimal bandwidths for below and above cut period 9 (May-June 2020) using T-RD. The number of observations for both analyses is n=7336 left of the cutoff and n=3668 right of the cutoff. The statistical significance is not changed; however, the coefficients change slightly from the MSE optimal with one optimal bandwidth selector for both above and below the cut period.

Sharp Time Regression Discontinuity (T-RD) using CER optimal bandwidth selector with Triangular Kernel			**Sharp Time Regression Discontinuity (T-RD) using MSE optimal bandwidth selectors for below and above the cutoff with Triangular Kernel**		
Pine chip-n-saw	**Left of Cutoff**	**Right of Cutoff**	**Pine Chip-n-saw**	**Left of Cutoff**	**Right of Cutoff**
Effective Number of Obs.	917	1834	Effective Number of Obs.	917	2751
Rho	0.273	0.273	Rho	0.469	1
	Coefficient	**Standard Error**		**Coefficient**	**Standard Error**
Conventional	-0.0689***	(0.0098)	Conventional	-0.0727***	(0 .0095)
Bias Corrected	-0.0519***	(0.0098)	Bias Corrected	-0.0568***	(0.0095)
Robust	-0.0519***	(0.0091)	Robust	-0.0568***	(0.0111)
Pine sawtimber	**Left of Cutoff**	**Right of Cutoff**	**Pine Sawtimber**	**Left of Cutoff**	**Right of Cutoff**
Effective Number of Obs.	917	1834	Effective Number of Obs.	917	2751
Rho	0.301	0.301	Rho	0.422	1
	Coefficient	**Standard Error**		**Coefficient**	**Standard Error**
Conventional	-0.0706***	(0.0095)	Conventional	-0.0740***	0.00914
Bias Corrected	-0.0592***	(0.0095)	Bias Corrected	-0.0584***	0.00914
Robust	-0.0592***	(0.0087)	Robust	-0.0584***	0.01092

*** p<0.1, ** p<0.05, ***p<0.01**