

Economics

Forest-Based Employment in the Southern United States amidst the COVID-19 Pandemic: A Causal Inference Analysis

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Abstract

In response to the COVID-19 pandemic, some governments instituted mandatory stay-at-home policies. As these policies made exceptions for essential industries such as the forest sector, it is not clear a priori whether and how these policies would affect forest-based employment. This study examined the effect of mandatory stay-at-home orders on employment in the forest sector in forest dependent counties in eleven southern states in the United States. We estimated panel event study models in addition to difference-in-difference models to evaluate the policy effects with respect to initial treatment as well as average effects to the treated counties during treatment. We found that employment in wood product manufacturing was lower on average in counties under a lockdown order compared with employment in counties without an active order. We also found that employment in the aggregate forest sector in counties that implemented the policy was significantly lower than employment in counties without the policy up to 9 months following initial enactment compared with the underlying difference between treated and control counties one month prior to treatment. Overall, our findings suggest that lockdown policies had a limited effect on employment in essential industries such as wood-based manufacturing sectors in the southern states.

Study Implications: This study uses causal inference techniques to assess the effect of lockdown orders on forest-based employment in 11 southern states. Results suggest effects of lockdown orders were limited to the aggregate forest sector and wood product manufacturing, likely due to the rapid designation of the sector as essential and the reduced production of sawmills. The other industries within the sector were not significantly affected, implying that industries designated as essential may be more resilient to short-term shocks. These findings can be used to inform discussions on potential policy responses to future disasters, including how different interventions interact with one another.

Keywords: stay-at-home orders, difference-in-difference, two-way fixed effect, panel event study, forest-dependent counties

The coronavirus disease of 2019 (COVID-19) caused by the virus SARS-CoV-2 emerged as a global pandemic in early 2020 (World Health Organization 2021). The World Health Organization (WHO) designated COVID-19 a global pandemic on March 11, 2020 (Lee and Yang 2022). As of March 2023, approximately one-third of the cases of COVID-19 in the United States, as well as deaths from the virus, have occurred in 11 southern states: 33% and 35%, respectively (Johns Hopkins University and Medicine 2023). In addition to loss of human life, the COVID-19 pandemic triggered a shockwave throughout the global economy. State and local governments made the decision to institute new policies, such as mandatory stay-at-home policies, to slow the spread of the virus. One of the many outcomes was a drop in employment across all sectors. Private sector employment dropped in the United States by approximately 25% in April 2020 compared with January 2020 (Chetty et al. 2022; Opportunity Insights 2022), whereas total civilian employment decreased by about

16% from January 2020 to April 2020 and did not rebound to pre-pandemic levels until December 2022 (Bureau of Labor Statistics 2023).

To limit the spread of infection as well as protect industries necessary to the US economy and population, governments were forced to delineate which industries were “essential” and shut down those deemed “non-essential” (Lindsey et al. 2020; Redlin 2022). As such, during the early lockdown weeks in March 2020, forestry and forest products industries were categorized as essential industries, or components of critical infrastructure, in the United States to ensure the supply of vital forest-based products (National Institute for Occupational Safety and Health 2021; Riddle 2021; U.S. Department of Homeland Security 2020). Wood-based products in high demand during this period included pulp- and fiber-based personal protective equipment (PPE) such as masks (Sen 2020), personal hygiene products, packaging materials (Liu et al. 2020), softwood lumber, and other

construction and building inputs (van Kooten and Schmitz 2022).

Despite the sector being almost entirely designated as critical infrastructure, forest-based employment and businesses were expected to experience mixed impacts throughout the pandemic. For example, del Rio-Chanona et al. (2020) predicted that logging equipment operators in the United States were likely to experience reduced work hours and increased unemployment early in the pandemic, potentially delaying income from harvests to forest landowners. In North Carolina, businesses in the logging and primary wood processing industries experienced 15% declines in total finished products during 2020 compared with 2019 (Parajuli and Bardon 2022); however, compared with 2019, North Carolina increased both softwood and hardwood harvest in 2020 (USDA Forest Service 2021). In the US South, Kline et al. (2021) reported consumption of wood by sawmills dropped during the second quarter of 2020 due to government shutdowns, fear, and market uncertainty. Furthermore, a survey of nonindustrial private forestland owners in the US South found that the COVID-19 pandemic would likely not change forest management or timber harvest activities on these lands (Hilsenroth et al. 2021). The uncertain effects in the forest sector seem to align with analysis of higher-level labor market trends, which found varying impacts according to timing and magnitude of state-level stay-at-home orders and by industry, whether designated as essential or not (Forsythe et al. 2020). For instance, Bruck et al. (2023) identified an overall decrease in prices of timber products in the US South soon after mandatory stay-at-home orders for all individuals in a jurisdiction were enacted; however, the researchers documented that a different policy, mandatory stay-at-home orders for certain areas of a jurisdiction, had varying effects on timber products.

The US South, known as the country's wood basket, has relatively high health, ecological, and social vulnerability compared with other regions of the country (Snyder and Parks 2020). Specifically, rural or nonmetropolitan communities constitute over half of the counties in the region, many of which are characterized as having persistent poverty and low education and employment levels¹ (USDA Economic Research Service 2019). Forests and forest-based goods and services have traditionally acted as a safety net to the rural poor (Sen 2020). In 2016, the southern United States supported over 496,000 employees directly in forestry, equating to over \$27 billion in wages in the region (Pelkki and Sherman 2020).

In this article, we aimed to quantify the effect of the COVID-19 pandemic on employment in the forest sector using the difference-in-difference (DID) and event study methods. Two studies have used the DID framework to assess the impact of the pandemic on employment in South Korea, a country that did not mandate a lockdown policy (Aum et al. 2021; Lee and Yang 2022). Aum et al. (2021) estimated the causal effect of localized outbreaks of COVID-19 on the labor market and found a one per thousand increase in infections decreased local employment by 2% to 3%. Meanwhile, results from the DID approach used by Lee and Yang (2022) suggest that the local variation in COVID-19 intensity explains only 9% of the 1.1 million jobs (4.2% of nonfarm employment) eliminated in the country in spring 2020. Hoehn-Velasco et al. (2021) used various causal inference techniques, including DID and event study approaches, to assess the effect of Mexico's Great Lockdown on formal

employment. Results from the DID analysis suggest that employment declined by over 5% on average during the first 9 months of the COVID-related recession, whereas findings from the event study imply that employment in the country remained 5% lower in November 2020 than pre-pandemic levels (Hoehn-Velasco et al. 2021).

The objective of this study was to evaluate the effects of pandemic-related policy interventions on forest-based employment in forest-dependent counties in the US South. To accomplish this, we used the DID and event study methodologies to assess the combined effects of state-level mandatory stay-at-home orders for all individuals and essential industries declarations on employment in the aggregate forest sector as well as each of the four industries that comprised the aggregate forest sector. We hypothesized that stay-at-home orders enacted during the pandemic would have differential effects on employment in the forest sector in forest-dependent counties depending on the specific industry, as not all were designated essential, and some may have characteristics that affected their ability to respond to other governmental mandates, such as social distancing requirements.

More specifically, we assumed stay-at-home orders may have had larger negative effects on employment in furniture manufacturing, as the industry was not completely designated as critical infrastructure, and other manufacturing industries that may have struggled to accommodate social distancing requirements. Accordingly, we were uncertain of the effects on employment in forestry and logging due to the findings reported by Hilsenroth et al. (2021) that landowners may not alter management and harvest activities, the high demand for many forest products (Liu et al. 2020; Sen 2020), and the temporary reduced consumption of logs by sawmills in the region (Kline et al. 2021). The results of this study could be used to inform discussions on potential policy responses to future disasters, including better information on how various policies interact. In the case of this study, we assessed how mandatory lockdown orders affected employment in a sector largely and quickly designated as essential. As such, our findings have implications on the resilience of essential industries to short-term economic shocks such as disasters and associated policy responses.

Methodology

Empirical Strategy

Following declarations made by the WHO and the US Federal Government, states in the United States responded by enacting lockdown policies. These policies varied in enactment date, duration, target population, and location (figure 1). For example, North Carolina's state government enacted a "Stay at Home Order" for all individuals from March 30, 2020 (North Carolina Office of the Governor 2020a) to May 20, 2020 (North Carolina Office of the Governor 2020b), whereas Arkansas never enacted a mandatory lockdown policy for all individuals (State of Arkansas 2022). We assumed that effects of state-level policies potentially varied at the county level. Therefore, we assessed policy effects at the county level. Translating the policies to treatments for the purpose of causal inference analysis, this means that counties that experienced the mandatory stay-at-home orders made up the treated group. Counties without an active policy represented the control group. As such, it is important to note that the control group includes (1) pure controls that

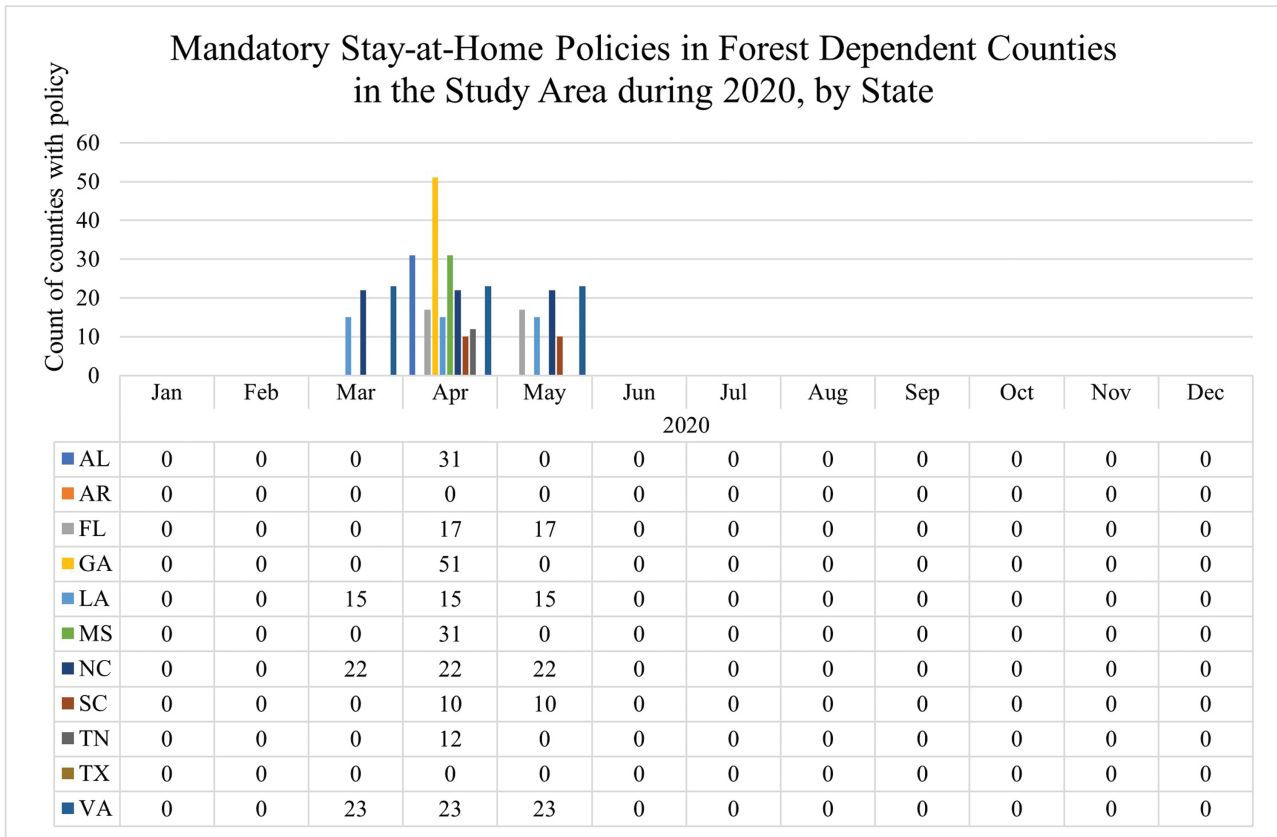


Figure 1 Counts of counties with mandatory stay-at-home policies, by state, during 2020 in the eleven-state study area: Alabama (AL), Arkansas (AR), Florida (FL), Georgia (GA), Louisiana (LA), Mississippi (MS), North Carolina (NC), South Carolina (SC), Tennessee (TN), Texas (TX), and Virginia (VA).

are never treated and (2) treated units when they are not actively receiving treatment.

To quantify the effect of the mandatory stay-at-home policies on employment in forestry-related industries and activities, we first used a DID or two-way fixed effects (TWFE) estimation approach for panel data (de Chaisemartin and D'Haultfoeuille 2020, 2022; Steigerwald et al. 2021). More specifically, we investigated the effects of the policy response on sector-specific employment by estimating the average treatment effects of the policy in forest-dependent counties in the US South. The DID estimation can be defined as (Steigerwald et al. 2021)

$$Y_{it} = \alpha_i + \delta_t + \beta^{DID} D_{it} + \theta Z_{it} + \varepsilon_{it}, \quad t = 0, \dots, T_i; \quad i = 1, \dots, N \quad (1)$$

where Y_{it} represents employment in forest-sector related industries in county i at time period t ; α_i is a county-level fixed effect; δ_t is a time fixed effect; β^{DID} , the parameter of interest, is the effect of a mandatory lockdown on employment or the average treatment effect on the treated; D_{it} is an indicator variable equal to 1 representing the mandatory lockdown period for all individuals and 0 otherwise; Z_{it} represent a vector of time-varying exogenous covariates affecting employment at the county level; and ε_{it} is the error term.

The observed outcome, Y_{it} , is related to the potential outcome framework and can be rewritten in a compact form as (Steigerwald et al. 2021)

$$Y_{it} = Y_{it}(0) + \tau_{it} D_{it}, \quad (2)$$

where $\tau_{it} = Y_{it}(1) - Y_{it}(0)$ is the treatment or causal effect for county i in period t , which is the difference between the outcome of the treated group ($Y_{it}(1)$) and the control group ($Y_{it}(0)$). As the potential outcomes pair consists of the observed outcome and the counterfactual, unobserved outcome, the treatment effect is not observable. Therefore, we define the average treatment effect on the treated (ATET) in period t , which is an average effect for treated counties in period t , as (Equation 3):

$$ATET_t = \mathbb{E}[\tau_{it} \mid D_{it} = 1]. \quad (3)$$

Additionally, because treatment time varied among groups, we were not able to test for no anticipation prior to treatment and parallel trends, which are key assumptions in the DID framework and when violated, biases the causal impact effect of the treatment. Although we were unable to formally test for anticipation of treatment, we assume no anticipation, as COVID-19 was a novel virus in early 2020. Accordingly, it is a reasonable assumption that nobody in the United States was expecting a stay-at-home policy in response to a pandemic in the first months of 2020. The parallel trends assumption states that the average outcome for the treated and control populations would have evolved in parallel without treatment, whereas the no anticipation assumption states that the treatment had no causal effect prior to its occurrence (Roth et al. 2022). As a result, we were able to test for pretrends using the coefficients on the lead variables representing differences between control and treated units during the time periods prior to initial treatment exposure.

Forest Dependent Counties in Study Area

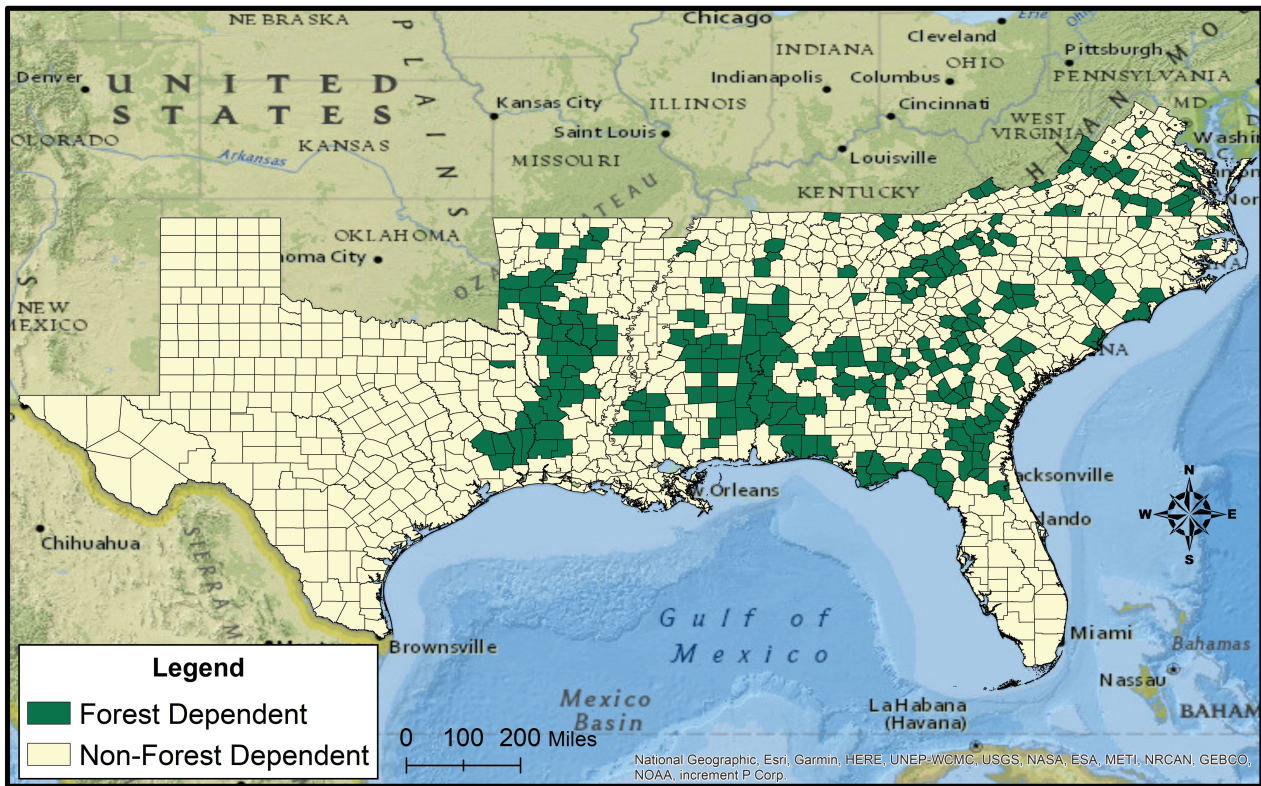


Figure 2 Map of forest-dependent counties in the eleven-state study region.

The event study methodology also assesses treatment effects that are dynamic in nature and is often used in conjunction with the DID approach (Clarke and Tapia-Schyte 2021; Sun and Abraham 2021). The panel event study design varies from the canonical DID approach, which estimates a single treatment effect, through estimating an individual treatment effect for each period in a window of time surrounding a defined event (Backhaus 2022). Clarke and Tapia-Schyte (2021) define the panel event study model as

$$Y_{it} = \alpha + \sum_{j=2}^J \beta_j (\text{Lead } j)_{it} + \sum_{k=1}^K \gamma_k (\text{Lag } k)_{it} + \mu_i + \lambda_t + X'_{it} \Gamma + \varepsilon_{it} \quad (4)$$

where Y_{it} is the occupation statistics in county i at time period t ; α is a constant; μ_i and λ_t are group and time fixed effects, respectively; X_{it} are time-varying controls; and ε_{it} is an unobserved error term. The leads and lags corresponding to the event of interest are binary variables signifying a given group's number of periods away from the initial treatment event in the respective time period. For instance, lead (2) takes a value of 1 when an observation is two time periods before initial treatment and 0 otherwise, whereas lag (3) takes a value of 1 when an observation is three time periods since initial treatment and 0 otherwise. Pure control groups, those that are never treated, take values of 0 in all lead and lag terms. The coefficients associated with lead and lag terms account for the difference between the control and treated groups. Significant T-statistics of the leads and lags provide evidence of pretreatment differences (leads) and posttreatment differences (lags). Lead (1), one period

before the event, is omitted to capture the baseline difference (Clarke and Tapia-Schyte 2021).

Recently, there has been discussion among econometricians about the validity of using the traditional DID framework to estimate the impact of heterogeneous treatment effects (Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfœuille 2020; Imai and Kim 2021). As a result, the DID framework can be extended to account for heterogeneous treatment effects such as variation in treatment timing (Roth et al. 2023). Due to treatment at the state level and other data-related characteristics, we also estimated various models that are detailed in Appendix A and the supplementary materials to check the robustness of the results of the DID and event study model estimations. These include triple differences models (DDD)² and model estimations using restricted datasets.

Study Area and Data

This study focused on the effect of the COVID-19 pandemic on forest-based employment in forest-dependent counties in eleven southeastern states (figure 2). We used the definition and identification of forest-dependent communities as described by Frey et al. (2022a, 2022b), which is based on the three pillars of sustainability: environmental, economic, and social. A county must have met the minimum requirements of one of the sustainability criteria to be categorized as forest dependent. Counties characterized under the environmental criterion qualified through the proportion of forested land in the county: a minimum threshold of 75% (Frey et al. 2022b). The economic criterion was based on a county's percentage of employment

and earnings in the forest sector: at least 10% of workers employed in the forest sector or more than 15% of earnings from the forest sector. The forest sector in Frey et al. (2022b) included North American Industry Classification System (NAICS) industry classes 113 (forestry and logging), 1142 (hunting and trapping), 1153 (support activities for forestry), 321 (wood product manufacturing), and 322 (paper manufacturing). Counties classified as culturally forest dependent featured an Indigenous population of at least 5% of the total population and a minimum of 30% forested land (Frey et al. 2022b).

Dependent Variables: Y_{it}

We obtained the NAICS level employment data from the Bureau of Labor Statistics (BLS), Quarterly Census of Employment and Wages (QCEW) (BLS 2022b, 2022c). The QCEW publishes estimations of monthly county-level employment, or the number of filled part-time, full-time, temporary, and permanent jobs, by NAICS classes. Employment counts include employees on “paid sick leave, paid holiday, paid vacation, and the like,” and exclude workers that are self-employed and workers that did not earn wages during the pay period including the 12th of the month due to “work stoppages, temporary layoffs, illness, or unpaid vacations” (BLS 2022a). This means that workers who were paid but did not report to work were still counted as employed. We focused our analysis on private-sector employment in NAICS classes 113 (forestry and logging), 321 (wood product manufacturing), 322 (pulp and paper manufacturing), and 337 (furniture manufacturing), all of which were designated essential except for several furniture manufacturing industries, in the study area from January 2017 to December 2020 (Table 1).

Table 1. All variables used in the study, along with their data sources.

Variable	Data Source or Details
Dependent variables	
Aggregate employment	BLS (2022b)
Forestry and logging employment	BLS (2022b)
Wood product manufacturing employment	BLS (2022b)
Pulp and paper manufacturing employment	BLS (2022b)
Furniture manufacturing employment	BLS (2022b)
Treatment variables	
Lockdown policy	CDC (2021b)
Time to treat	Generated
Covariates	
Percentage COVID	CDC (2022a) and U.S. Census Bureau (2023)
Apple Mobility	Apple (2023)
Rainfall	NOAA (2021)
Ashley County	Generated
Aggregate establishment	BLS (2022b)
Forestry and logging establishment	BLS (2022b)
Wood product establishment	BLS (2022b)
Pulp and paper establishment	BLS (2022b)
Furniture establishment	BLS (2022b)

BLS, Bureau of Labor Statistics; CDC, Centers for Disease Control and Prevention; NOAA, National Oceanic and Atmospheric Association.

We summed employment in each of the industries across counties to represent the aggregate forest sector in the study region. We performed natural log transformations to reduce heteroscedasticity in our exploratory analysis as well as to simplify interpretation of the results.

It is important to note that the BLS changed the input methodology used for industry nonresponses in November 2020 (BLS 2021). Prior to November 2020, monthly employment was imputed by multiplying the previous month's employment by the ratio of that establishment's over-the-month change from the previous year. Because the previous methodology did not consider any changes in economic condition in the current year, the BLS adapted the procedure through three improvements to account for the impacts of COVID-19. The first improvement calculated a nonresponding establishment's current month's employment using the product of the nonrespondent's previous month's employment and the current monthly change ratio of employment in similar businesses. The second improvement used counts of unemployment benefit claims aggregated by an employer to identify employers that are likely to have ceased operations. Lastly, the third improvement involved the use of benefit claims counts by the state QCEW as a supplement to manual data review (BLS 2021).

Treatment Variables: D_{it} , $(Lead\ j)_{it}$, and $(Lag\ k)_{it}$

We used COVID-19 stay-at-home policy data from the Centers for Disease Control and Prevention (CDC) (CDC 2021a). As county-level responses were only available until May 5, 2020 (CDC 2021b), we instead used state and territorial orders by county that covered the period March 15, 2020 to August 15, 2021. This is a noteworthy caveat because typically the treatment should occur at the unit or group level when using the DID estimator, which for this study is the county level.

Of the eleven states in the study region, nine implemented lockdown policies between March and May of 2020, which affected 212 forest-dependent counties in the southern nine states (figure 1). Counties in Louisiana, North Carolina, and Virginia experienced mandatory stay-at-home policies during March, April, and May 2020, whereas counties in Florida and South Carolina experienced mandatory stay-at-home policies during April and May 2020. Further, counties in Alabama, Georgia, Mississippi, and Tennessee were only under mandatory stay-at-home orders for all individuals during April 2020. Counties in Texas and Arkansas never experienced mandatory stay-at-home orders for all individuals during 2020, serving as a control scenario in our analysis.

For D_{it} , we used a treatment variable based on the CDC dataset: (1) *stay-at-home*. The binary variable *stay-at-home* only takes a value of 1 for counties with an active mandatory stay-at-home policy and 0 otherwise. In addition, we generated a fixed-effects variable to account for each month in our dataset, which takes values from 1 to 49, where 1 represents January 2017 and 49 represents December 2020. We specified this determinant as an indicator variable in the model, which created dummy variables for each month, with month 1 being omitted to overcome a dummy variable trap. In terms of the month variable, the mandatory stay-at-home orders occur at values 39, 40, and 41. Further, we created the variable *time to treat* using the month variable and the policy treatment variable to account for the number

of months before or after initial treatment, a variable necessary for the panel event study models to generate the lead and lag variables in equation 4. Therefore, only treated counties contain values for *time to treat* and initial treatment occurs at *time to treat* = 0.

Independent Variables: X'_i

Additionally, we included percentage of the population with COVID-19 using data from the CDC and Census Bureau to capture local infection rates. Percentage of the population with COVID-19 was calculated by dividing the total number of cases in a month last reported by the CDC by the estimated population for a county in 2020 and then multiplying by 100 (CDC 2022a; U.S. Census Bureau 2023). Because we were unable to get monthly county-level population data, we estimated the percentage of each county infected with COVID-19 by using the yearly population estimate as the denominator and monthly COVID-19 cases as the numerator (we assumed that total county population did not change significantly from month to month). Furthermore, some counties overestimated daily COVID-19 cases and corrected the estimate later. For this reason, we used the number of daily cases reported at the end of each month to reduce measurement error.

Furthermore, we gained access to the publicly available Apple Mobility data provided by Apple Inc., who estimated driving directions requests above or below an average baseline (baseline levels were determined by Apple Inc.) (Apple 2020, 2023). We then calculated average mobility above or below baseline for each county by month. Noteworthy, the data does not capture directions requests of individuals who do not have an iPhone and does not count trips taken without driving requests. Yet iPhones are widely used across the United States (approximately 34% of the US population

in 2020) (Ruby 2023), and Apple Mobility data has been used to explore the impacts of COVID-19 on social distancing and reduction in travel by car (Cot et al. 2021; Kurita et al. 2021).

Additionally, to control for number of business establishments, we incorporated the count of private establishments by NAICS industry that responded to the BLS QCEW (BLS 2022a). We aggregated the number of establishments across each of the four industries of interest to include in the aggregate forest sector model. We expected number of establishments to be positively correlated with employment counts. Further, we used rainfall, or precipitation in inches (National Oceanic and Atmospheric Association 2021), as a covariate to partially capture the environmental effects on forest-based employment because high rainfall tends to affect forest management activities such as chemical treatments and harvest (Stanturf et al. 2007; Wiener et al. 2020). We also performed natural log transformations on the establishment count and rainfall variables.

Finally, we created a binary variable representing Ashley County, Arkansas. This variable takes a value of 1 for all observations in Ashley County beginning October 2019 and 0 otherwise. In October 2019, employment in pulp and paper manufacturing increased in Ashley County, Arkansas, likely due to a mill that transitioned from bleached paper board to tissue and towel production (Georgia-Pacific 2019; Matthis 2019).

Results

The forest-dependent counties in the pure control states, Arkansas and Texas, exhibit similar characteristics to the forest-dependent counties in the states that experienced mandatory stay-at-home orders in terms of forest sector significance and aggregate forest area, population, and income (Table 2). Specifically, total forest area and average

Table 2. Total forest area, total population, average per capita income, average percentage of pay in the forest sector, and average percentage of employees in the forest sector in forest dependent counties in the eleven-state region (Frey et al. 2022a).

State	Total forest area, acres ^a	Total population ^b	Average per capita income, \$ ^c	Average percentage of pay in forest sector, % ^{b,c,d}	Average percentage of employment in forest sector, % ^{b,c,d}	Number of forest dependent counties
Treated states						
Alabama	12,603,553	921,142	21,416.52	9.10	7.62	31
Florida	6,255,526	797,141	22,571.18	8.86	7.01	17
Georgia	10,515,452	780,910	21,536.06	6.89	5.16	51
Louisiana	6,141,295	371,631	21,272.43	13.02	9.45	14
Mississippi	9,465,674	526,982	20,112.48	9.29	8.03	31
North Carolina	5,164,635	927,538	23,465.73	4.28	3.35	22
South Carolina	2,855,826	262,009	21,825.30	7.66	6.37	10
Tennessee	2,306,145	252,909	21,094.92	10.45	8.31	12
Virginia	4,918,015	365,808	26,588.48	8.12	6.86	23
Pure control states						
Arkansas	9,262,532	459,528	21,899.71	12.80	9.73	24
Texas	7,832,328	224,346	25,358.00	9.48	5.63	14 ^e

Original sources reported by Frey et al. (2022a):

^aUS Forest Service, Forest Inventory and Analysis (2020);

^bUS Census Bureau, American Community Survey (2020);

^cCenters for Disease Control and Prevention, Social Vulnerability Index (2018);

^dUS Census Bureau, Annual Economic Survey (2020).

^eSeven counties in Texas are spatially forest dependent but do not employ workers in the forest sector.

per capita income in forest-dependent counties in the pure control states was within the range of total forest area and income values documented for forest-dependent counties in the treated states; however, total population in forest-dependent counties in Texas was slightly less than the populations in other states in the study region (Table 2). Similarly, although the average share of labor income from the forest sector in forest-dependent counties in Arkansas and Texas were within the range of values reported for the nine other states, the average percentage of forest sector employment in forest-dependent counties in Arkansas was slightly higher than the values associated with the other states (Table 2).

Of the 249 forest dependent counties in the eleven-state study region, 242 counties employ workers in the forest sector. Seven of the fourteen forest dependent counties in Texas qualify as spatially dependent but do not report having private employment in the forest sector. Furthermore, average employment and number of establishments that responded to the QCEW in the aggregate forest sector, forestry and logging (NAICS 113), and wood product manufacturing (NAICS 321) were greater in the pure control counties than in treated counties prior to and following March 2020 (Table 3). Following March 2020, average employment in the pure control counties was greater in pulp and paper manufacturing (NAICS 322), which increased four-fold. Conversely, average employment in furniture manufacturing (NAICS 337) and number of private establishments in pulp and paper manufacturing (NAICS 322) and furniture manufacturing (NAICS 337) were lower in the pure control counties than in treated counties before and after March 2020.

Average employment in control and treated counties appears to follow similar trends prior to the COVID-19 pandemic for three of the four forest-based industries: forestry and logging, wood product manufacturing, and furniture manufacturing (figure 3). However, average employment in pulp and paper manufacturing in the control counties increased in October 2019 whereas average employment in the industry in the treated counties remained relatively stable. This discrepancy is likely a result of the mill transition in Ashley County, Arkansas. The supplementary materials (Figure S2.1, Table S2.1, and Table S2.2) feature results from model estimations using a dataset that omits Ashley County.

We estimated five different models, each associated with the aggregate forest sector or one of the four industries of interest. For robustness, we also estimated additional models using the full 2017–2020 dataset including triple-differences where we clustered standard errors at the state level (Appendix A), as well as using a dataset restricted to the years 2019–2020 (Supplement 1). The results associated with the alternative estimations are comparable to the results described below in terms of relationships with the dependent variable and significance.

All else held constant, employment in wood product manufacturing (NAICS 321) was 19% lower on average in counties with mandatory stay-at-home orders while the policy was in effect (Table 4) in comparison with employment in counties that never experienced the policy and treated counties while the policy was not in effect. However, the estimated effect should be taken with caution as it was weakly significant (10% significant level) in the DID model and not significant in the DDD model (Appendix A) or the

Table 3. Sample means and standard errors of county-level employment and business establishment count relative to March 2020 and by treatment group, where the Control group represents units that are never treated.

Sector/industry	January 2017–February 2020		March 2020–December 2020		January 2017–February 2020		March 2020–December 2020	
	Control	Treated	Control	Treated	Control	Treated	Control	Treated
	Employment, mean (SE)				Establishment count, mean (SE)			
Aggregate: all industries	257.44 (9.04)	229.72 (4.51)	300.43 (20.76)	223.93 (8.71)	17.54 (0.35)	13.60 (0.12)	17.33 (0.68)	13.22 (0.22)
Forestry and logging, NAICS 113	63.86 (2.18)	55.51 (0.81)	61.98 (4.37)	53.84 (1.57)	11.73 (0.29)	8.46 (0.09)	11.76 (0.57)	8.20 (0.17)
Wood product manufacturing, NAICS 321	191.08 (7.73)	141.00 (3.35)	214.45 (16.79)	142.51 (6.90)	5.10 (0.09)	4.03 (0.04)	4.85 (0.15)	4.05 (0.08)
Pulp and paper manufacturing, NAICS 322	14.16 (4.75)	33.86 (2.53)	65.86 (19.46)	36.37 (5.25)	1.71 (0.05)	1.82 (0.02)	1.67 (0.09)	1.79 (0.05)
Furniture manufacturing, NAICS 337	9.29 (1.44)	76.90 (4.64)	7.77 (2.35)	69.23 (8.01)	2.57 (0.19)	3.07 (0.06)	2.57 (0.39)	3.01 (0.11)

NAICS, North American Industry Classification System.

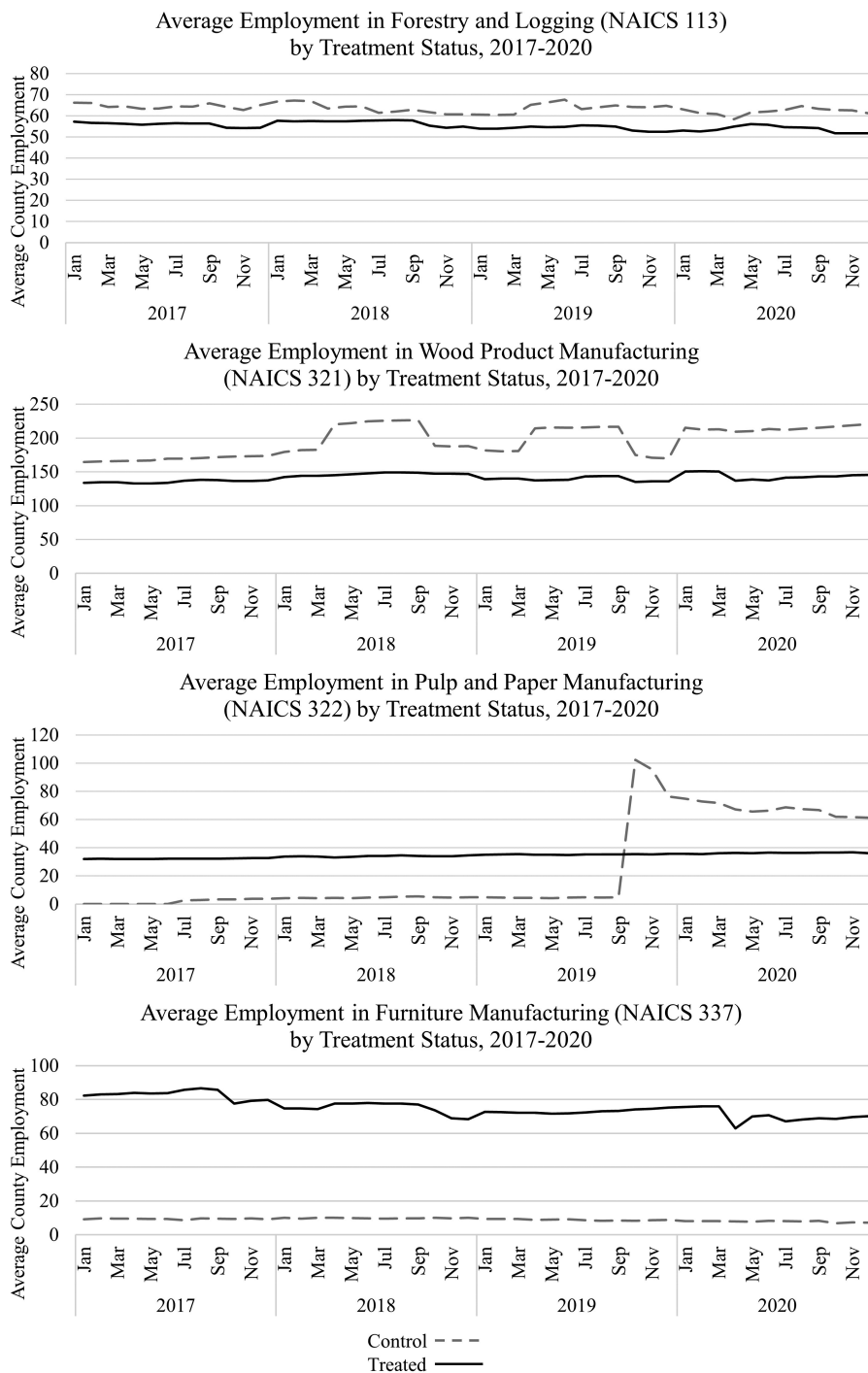


Figure 3 Average employment by North American Industry Classification System (NAICS) class and treatment status where the solid lines represent the treated groups and the dashed lines represent the pure control groups (those never treated).

models using the dataset restricted to 2019–2020 (Table S1.2 and Table S1.3). The estimated ATET, or DID estimator, was insignificant in all other models except for the DDD model for employment in furniture manufacturing (NAICS 337) using the full dataset (Appendix A). In this case, employment in counties that experienced the policy was 9% higher on average than employment in counties without the policy in effect. Insignificant ATET estimates implied that the mandatory stay-at-home orders did not have a statistically significant effect on forest-based employment in the counties in the study region.

Interestingly, percentage of the population with COVID-19 was found to be positively correlated with employment in the aggregate forest sector at the 10% significance level in the DID and DDD models (Table 4 and Appendix A) as well as the DID and DDD models using alternative datasets (Table S1.2, Table S1.3, and Table S2.2). Meanwhile, the variable was negatively correlated with employment in pulp and paper manufacturing (NAICS 322) at the 10% significance level in the DDD model using the full dataset. We also found that the binary variable associated with the mill transition in Ashley County, Arkansas, was positively correlated with employment

Table 4. Effects of mandatory stay-at-home orders on monthly employment (logarithm scale) in the forest sector and each industry in forest dependent counties in the eleven-state study region, 2017–2020.

	(1)	(2)	(3)	(4)	(5)
	Aggregate employment	Forestry and logging	Wood product manufacturing	Pulp and paper manufacturing	Furniture manufacturing
ATET ¹					
Lockdown policy	-0.04 (0.03)	0.12 (0.08)	-0.19* (0.11)	0.09 (0.08)	0.09 (0.08)
Controls					
Percent COVID	0.04* (0.02)	0.01 (0.04)	0.04 (0.05)	-0.05 (0.03)	0.02 (0.05)
Apple Mobility	-0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Rainfall (logarithm)	-0.01 (0.00)	-0.00 (0.02)	-0.01 (0.02)	-0.01 (0.01)	-0.00 (0.01)
Ashley County	1.46*** (0.02)			6.73*** (0.02)	
Aggregate establishment (logarithm)	0.72*** (0.13)				
Forestry and logging establishment (logarithm)		1.04*** (0.24)			
Wood product establishment (logarithm)			1.02*** (0.23)		
Pulp and paper establishment (logarithm)				0.26 (0.21)	
Furniture establishment (logarithm)					0.74*** (0.22)
Constant	3.06*** (0.33)	0.94** (0.44)	1.30*** (0.29)	0.34** (0.12)	0.68*** (0.18)
Treated counties	176	193	194	78	117
Control counties	28	29	31	12	12
N	8721	10482	10383	4065	5622

ATET, Average treatment effect on the treated.

Robust standard errors in parentheses clustered at county level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.001$.

in the forest sector and pulp and paper manufacturing (NAICS 322) for each of the estimated models. Finally, business establishment count was significantly and positively associated with employment in the aggregate forest sector and each of the industries other than pulp and paper manufacturing (NAICS 322), which was insignificant.

The event study plots visually demonstrate the high variability in employment in the forest sector and each industry, as can be inferred through the large confidence intervals, before and after treatment, where initial treatment occurs at $t = 0$ (figure 4). Aggregate employment in the forest sector in treated counties was significantly less than aggregate employment in counties without a policy up to 9 months following initial enactment in March or April 2020 (Appendix B). During this time, employment was 4% to 11% lower in treated counties than counties without a policy as compared with the prevailing difference in employment between treated and control counties 1 month before initial treatment. In other words, employment in the forest sector in counties that experienced a mandatory stay-at-home order was 4% less than employment in the sector in counties without the specific policy 1 month after the policy was enacted. Furthermore, employment in wood product manufacturing (NAICS 321) was also significantly less in treated counties at lags 4 (-0.27), 7 (-0.25), and 8 (-0.19) compared with the prevailing difference between groups at lead 1. Of note, employment in furniture manufacturing (NAICS 337) in counties with a mandatory stay-at-home order was significantly greater during lag 5 (0.43) and significantly less during lag 6 (-0.40) than counties without the policy, based on the underlying difference between groups 1 month before initial treatment. We found similar effects on employment in the forest sector and industries in models estimated with the alternative datasets (Table S1.1 and Table S2.1).

Additionally, we reject the null hypothesis that the coefficients on the leads are equal to zero for aggregate employment (2017–2020 dataset and dataset omitting Ashley County) as well as employment in forestry and logging (NAICS 113) (2017–2020 dataset) (5% significance level). In other words, treated and control units were jointly and significantly different before the treatment, challenging the parallel trends assumption needed to interpret the treatment effect as a causal impact. However, T-statistics for all leads, except for leads 5 and 4 (forestry and logging, NAICS 113), associated with the models for aggregate employment and employment in forestry and logging (NAICS 113) were insignificant (Appendix B and Table S1.1). Further, joint significance tests for event leads using the dataset restricted to the years 2019 and 2020 produced insignificant F-statistics for each employment model. The T-statistics associated with the coefficients on leads 5, 4, and 2 for the forestry and logging (NAICS 113) employment model using the 2019–2020 data were also significantly negative, implying employment in the industry in treated counties was lower than employment in control counties prior to treatment. Consequently, we interpreted the results conservatively.

Discussion and Conclusion

The COVID-19 pandemic led to various policy responses by county, state, and federal governments. Some states in the United States enacted mandatory stay-at-home orders for all individuals to limit social interactions and thus community spread of the virus. These lockdown orders were relaxed relatively early in the pandemic and largely replaced with recommended stay-at-home orders (CDC 2021a; Redlin 2022). The US Federal Government responded to the pandemic by designating industries essential to the US economy

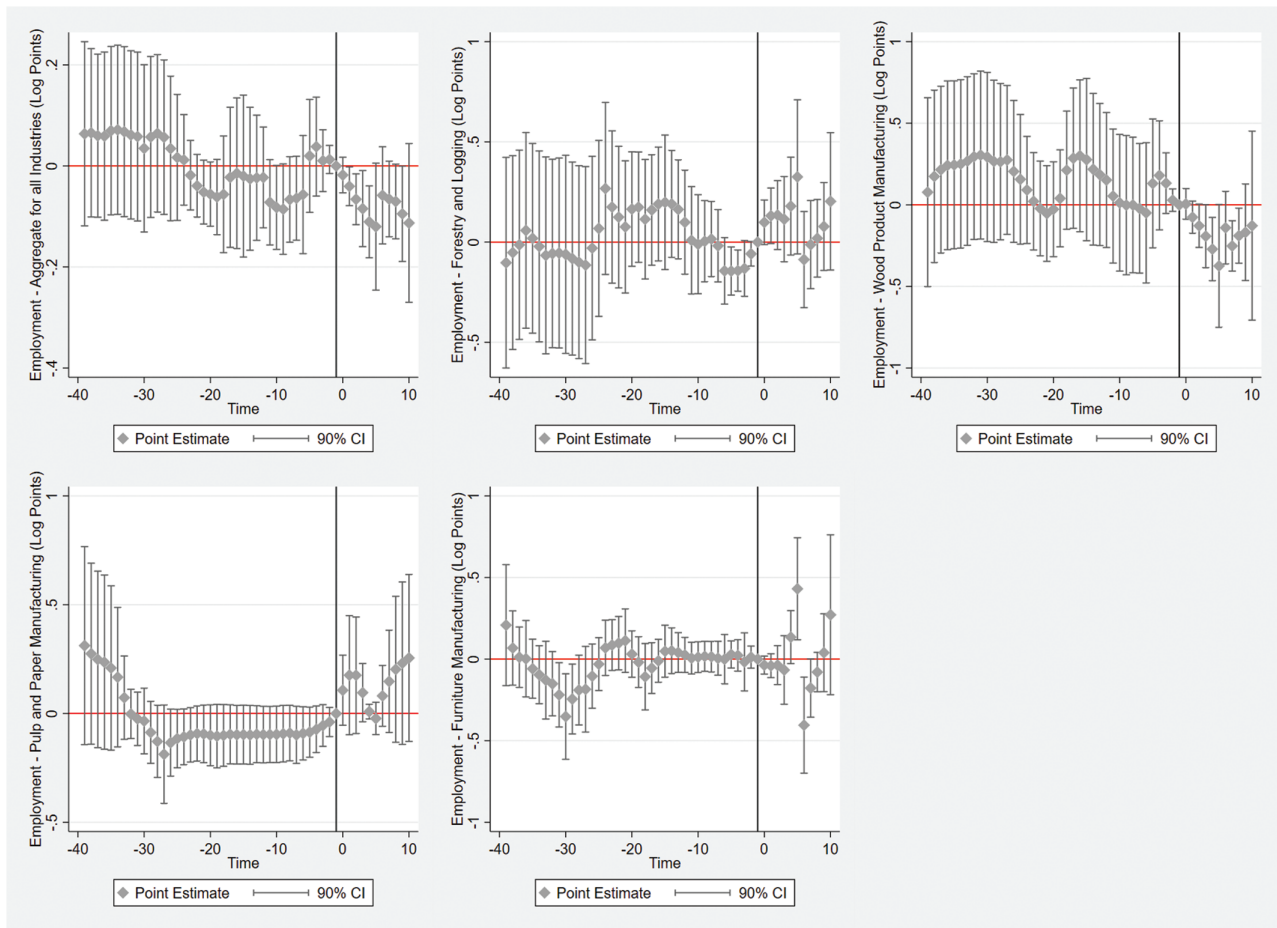


Figure 4 Panel event study point estimates and 90% confidence intervals (CI) for monthly employment in the forest sector and individual industries in forest dependent counties in the eleven-state study region, 2017–2020.

such as forestry as “critical infrastructure,” potentially offsetting the effects of mandatory stay-at-home orders on these industries. This study evaluates the combined effect of mandatory stay-at-home orders and designation as essential on employment in the forest sector in forest-dependent counties. We assessed the combined effects in forest-dependent counties in an eleven-state region in the southern United States using two approaches: the DID, or traditional TWFE, and the panel event study design detailed by [Clarke and Tapia-Schyte \(2021\)](#), which accounts for variation in treatment timing.

The results suggest that mandatory stay-at-home policies had limited effects on the various industries in the forest sector in the study region. Specifically, the findings suggest that the pandemic policies did not significantly affect employment in forestry and logging (NAICS 113), pulp and paper manufacturing (NAICS 322), or furniture manufacturing (NAICS 337). However, our results do show that the specific policies led to a significant decrease in employment in the aggregate forest sector and wood product manufacturing (NAICS 321) in treated counties compared with counties without a mandatory lockdown order in effect. These decreases were higher than those reported for the entire forest sector in the United States, which range from 1% to 3% ([Kline et al. 2021](#); [Prestemon and Guo 2022](#)).

[Kline et al. \(2021\)](#) documented that consumption of wood by sawmills decreased during the second quarter of 2020 due to shutdowns, as well as market uncertainty associated with

the pandemic. In addition, mills struggled to replace skilled laborers that were infected by COVID-19, so much so that some were forced to shut down for 2 to 6 weeks ([Kline et al. 2021](#)). During that time, some mills temporarily ceased or reduced operations to implement new safety procedures and secure access to PPE ([Popken 2021](#)). Although we were unsure of how wood consumption changes were distributed across the states in our study, it may be possible that sawmills in counties that had a stay-at-home policy reduced their productivity more than mills that sourced their materials from counties without a stay-at-home policy. Unlike [Kline et al. \(2021\)](#), our panel event study results suggest that disruptions to the forest sector were not necessarily resolved by the third or fourth quarter of 2020.

The panel event study design allowed us to assess the employment effects at various time periods, compared with the treatment effects estimated using the standard DID approach, which are averaged over the treatment period. Findings from the event study indicate aggregate employment in the forest sector was 4%–11% less in counties that experienced a lockdown policy than counties without an active policy up to 9 months after March/April 2020 compared with the prevailing difference 1 month before policy enactment. During this time, hospitalizations and deaths attributed to the COVID-19 pandemic in the southern United States were reaching unprecedented levels ([Johns Hopkins University and Medicine 2022](#)). Although we did not include hospitalizations or deaths as

covariates, we did incorporate percentage of the population with COVID-19 as an independent variable. Percentage of the population with COVID-19 was weakly significant and positive in the aggregate employment model, implying that increasing cases of infections were not correlated with lower employment in the sector.

When decomposing employment by industry, we found that employment in wood product manufacturing (NAICS 321) was 19%–27% less in counties that experienced a mandatory stay-at-home order up to 8 months following the passage of the lockdown orders. Interestingly, employment in furniture manufacturing (NAICS 337) was significantly higher in treated counties 5 months following initial exposure to treatment and significantly lower the following month, compared with employment in control counties 1 month before treatment. These findings suggest that either employment effects from stay-at-home orders are delayed or, similar to the findings presented by [Aum et al. \(2021\)](#), there are other factors influencing employment in the forest sector such as fear of infection, public health measures, COVID-related policies, or novel government programs such as the Paycheck Protection Program (PPP). We estimated the DID models using other policy measures as treatments such as recommended stay-at-home orders and did not find significant effects on employment.

We did not incorporate a variable controlling for county-level PPP loan totals, which may have helped to explain employment impacts after mandatory stay-at-home orders were lifted. For example, the second and third rounds of loans were provided between April 27 and August 8, 2020, (round 2) and after December 27, 2020 (round 3) ([Russell 2022](#)). Forest product companies across the country received \$4.7 billion in PPP loans, 68% of which went to logging and wood product manufacturing companies ([Russell 2022](#)). In the eleven-state study region during 2020, these loans allowed forest product companies to support almost 177,000 jobs in forestry and logging, wood product manufacturing, pulp and paper manufacturing, and wood furniture manufacturing, excluding self-employed jobs ([U.S. Small Business Administration 2022](#)).

The findings presented in this study hinged on the DID modeling assumptions including parallel trends and no anticipation of treatment ([Clarke and Tapia-Schythe 2021](#); [Goodman-Bacon 2021](#)). Employment in the control and treated counties in the study region in pulp and paper manufacturing (NAICS 322) appeared to experience differing trends (e.g., employment in the control counties sharply increased in the fall of 2019) ([figure 3](#)). Nonetheless, the leads prior to initial treatment were insignificant when omitting Ashley County, Arkansas ([figure S3.1](#) and [Tables S3.1 and S3.2](#)), providing support of parallel trends. This study was also constrained by the number of pure control units that never experienced a mandatory stay-at-home policy for all individuals, forest-dependent counties in Arkansas and Texas; however, in the DID models, counties not actively receiving treatment also acted as controls, which provides a sufficient pool of control units for the purpose of this analysis. We considered supplementing with the synthetic control method to assess the robustness of our analysis. However, the synthetic control method is more applicable to studies with a limited number of treated units, rather than control units, because it requires a pool of donor units large enough to calculate the synthetic control ([Abadie 2021](#)).

Similarly, the BLS QCEW employment data is accompanied with its own potential caveats. For instance, changing the imputation methodology for nonresponses may create noise in the data. Further, the imputation strategy change was implemented around the same time the United States was experiencing an increase in COVID-19 cases ([Johns Hopkins University and Medicine 2022](#)). Also, the BLS QCEW excludes individuals who are self-employed and workers that did not earn wages during the pay period including the 12th of the month due to “work stoppages, temporary layoffs, illness, or unpaid vacations” ([BLS 2022a](#)). We recommend that future research use a different employment dataset to compare with the findings observed in this study.

Additionally, this analysis does not include data after December 2020. The logging industry was specifically targeted in the Consolidated Appropriations Act of 2021. The policy allowed logging companies that experienced a minimum 10% loss in gross revenue in 2020 compared with 2019 to apply for relief payments of up to \$125,000 per company ([USDA 2021a, 2021b](#)). Future research could incorporate data from 2021 and on to assess the effects of alternative policy responses such as the Pandemic Assistance to Timber Harvesters and Haulers (PATHH) program on forest-based employment.

Furthermore, this study explores the effects of the mandatory stay-at-home policy for all individuals in forest-dependent counties on forest-based employment in eleven states in the US South. Future research could account for all active policies and programs, including the PPP, to determine whether implementing a suite of responses affects employment differently than a single active policy. Also, because the CDC county-level response dataset was not available for the entire study period, we used the state-level policy dataset. This is not ideal, as the DID framework recommends assessing units as the treatment level; however, we feel confident in our findings, as clustering standard errors at the state level instead of the county level did not significantly alter our results. Similarly, this analysis did not account for spillover effects, such as when a treated county neighbors a control county. Future research could incorporate covariates that capture these effects or estimate a spatial autoregressive model.

In conclusion, our study highlights the complexities surrounding the effects of pandemics and pandemic-related policies on employment in the forest sector. We found that lockdown policies had largely limited effects on forest-based employment, which was almost entirely categorized as essential in early 2020. Nonetheless, our analysis did find evidence, although weakly significant in most cases, of negative effects on employment in the aggregate forest sector and wood products manufacturing. Similar to the findings of other studies ([Aum et al. 2021](#)), mandatory lockdown orders were not the sole explanation behind job loss, as employment significantly decreased in various industries after lockdowns were lifted. Therefore, the results of this study provide insights on the resilience of essential industries, such as those in the forest sector, to short-term economic shocks. More specifically, although lockdown orders had a limited effect on average employment in counties while under the policy, the industries were not completely immune to negative impacts that occurred after lockdown orders were lifted. Examining attributes and potential trends related to industries that were and were not negatively affected may help to inform

policymakers on how to effectively address disasters while protecting the economy.

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Conflict of Interest

None declared.

Endnotes

¹The Economic Research Service (2019) classifies a county as (1) in persistent poverty if at least 20% of its residents are categorized as poor over three decades, as measured by the 1980, 1990, and 2000 decennial censuses and the American Community Survey 5-year estimates for 2007–2011; (2) having a low educational level if at least 20% of its residents aged 25 to 64 did not have a high school diploma or equivalent between 2008 and 2012; and (3) having a low employment level if less than 65% of its residents age 25 to 64 were employed in 2008–2012.

²In the case of this study, the triple differences model (DDD) is specified as below where Y_{ist} represents occupation statistics in county i and state s at time period t , β^{DDD} is the parameter of interest, D_{it} is an indicator of treatment, $State_s$ is a categorical variable for the state, γ_{it} are county-time fixed effects, δ_t are time fixed effects, λ_i are county fixed effects, Z_{ist} are covariates, and ε_{ist} is the error term (Ferris and Frank 2021).

$$Y_{ist} = \beta^{DDD} D_{it} \times State_s + \gamma_{it} + \delta_t \\ \times State_s + \lambda_i \times State_s + \theta Z_{ist} + \varepsilon_{ist}, \\ t = 0, \dots, T; i = 1, \dots, N; s = 1, \dots, S.$$

Supplementary Materials

Supplementary data are available at *Forest Science* online.

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