What Drives the Change in Employment in the US Logging Industry? A Directed Acyclic Graph Approach

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Abstract

Employment in the US logging industry has been declining over the past few decades and fell to a 20-year low following the 2008 economic recession. This study investigates the drivers of employment in the US logging industry from 2007 to 2017, using a directed acyclic graph (DAG). This approach is applied for the first time to disclose the contemporaneous causal relations among employment, wages, mechanization, production level, and product prices in the logging industry. Forecast error variance decomposition (VD) is further used to examine the long-run dynamic relationships between these variables. The results show that the product price directly affects employment and indirectly promotes employment through wages. The results of VD show that mechanization has an increasing long-term effect on employment.

The logging industry is an integral part of the forest industry, providing raw materials (for example, sawn wood and wood chips) to the wood processing industry. Across the globe, forestry plays an essential role in the rural economy, including in the United States (He et al. 2020, Jolley et al. 2020, Li et al. 2021). The logging industry is estimated to contribute around $36.2 billion to the economy and opened up about 488 thousand jobs in the United States (Jolley et al. 2020). In the Northern Forest region, the logging industry employed approximately 11,000 employees and provided valuable jobs for the rural communities, where no other jobs were available (Leon and Benjamin 2012). The logging industry in Maine generates good job opportunities in the rural areas where the chances of being employed are sparse (Taggart and Egan 2011). The logging industry in Maine is estimated to contribute $619 million toward output, 9,000 jobs, and $342 million in labor income in 2017, including lumber transport jobs as well (Bailey et al. 2020).

Although the logging industry generated thousands of jobs in the past, employment in the logging industry has declined across the United States in recent years. Most of the logging industry is located in the West and the South. However, these regions also saw a massive decline in their employment numbers. Employment in the logging industry has fallen by an average of 2 percent per year since 1997 (see Fig. 1; US Census Bureau 2021). Oregon provides the most prominent employment opportunity throughout the United States. Logging employment in Oregon dropped from 7,727 in 1997 to 7,408 in 2002 and declined further from 6,631 in 2007 to 5,262 in 2017 (US Census Bureau 2021). In 2002, Alabama had the largest logging employment in the South, with 5,133 jobs, while Georgia came in second at 4,968. Georgia surpassed Alabama as the state with the most logging jobs in 2017, but the logging

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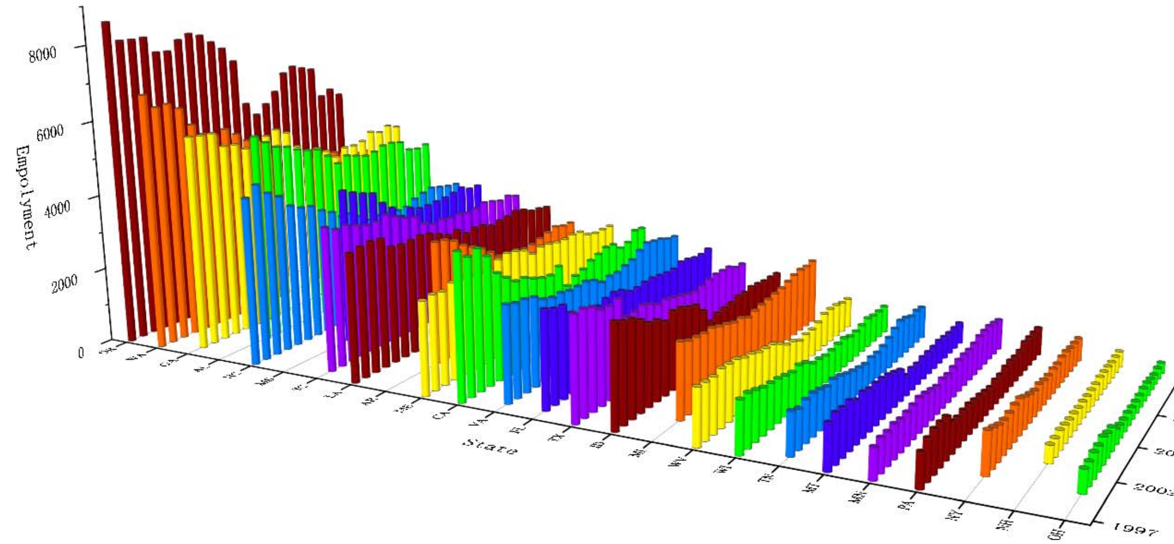

Figure 1.—Employment in logging industry across the United States, 1997 to 2019 (US Census Bureau 2021).

employment numbers in both states fell to 3,994 and 3,772, respectively (US Census Bureau 2021).

Previous research in the logging industry mainly focused on one single factor, such as demography, employment, mechanization, or production level. These studies focused on the pairwise directional connectedness between any two of the abovementioned variables. For example, Allred et al. (2011) surveyed Midwest logging firms. They applied principal component analysis (PCA) and analysis of variance (ANOVA) to investigate the influence of mechanization on the cost and profitability of the logging industry. Baker and Greene (2008) conducted a survey in Georgia and, using statistical analysis, found that mechanization increases production per person-hour and the efficiency of the human capital. The research in logging employment also focused on pairwise directional connectedness between employment and one other variable. For example, Abbas et al. (2014) analyzed the employment and mechanization in the logging industry in Michigan and Wisconsin by statistical analysis and found that the decreased production level resulted from the shutdown of the pulp and paper industries leading to the logging equipment operators leaving the industry. Jacobson et al. (2009) collected data via focus groups and a survey questionnaire in Pennsylvania and found that the production level partly affected employment through statistical analysis. Lee and Eckert (2002) had a similar conclusion based on statistical analysis to study the logging industry in the states of Washington and Oregon in the United States and Japan. Shivan et al. (2020) investigated the status of the logging industry in Michigan, Minnesota, and Wisconsin via descriptive and inferential statistical techniques. They found that wages and benefits have a positive impact on employment. He et al. (2021), by estimating labor productivity, argued that mechanization was one of the main reasons for declining employment . Duc et al. (2009) used the data from a mail survey in Alabama to regress production functions to identify the elasticity between employment and capital and found that elasticity was unitary. Some comprehensive studies systematically describe various aspects of the logging industry (Boltz et al. 2003, Conrad and Greene 2017, Moskalik et al. 2017, Conrad et al. 2018), but most are literature reviews without empirical evidence.

In reality, however, the labor market in the logging industry depends on both demand and supply. From the demand side, the total removal of the forest resources is associated with the degree of mechanization and the business cycle, particularly the housing market, building permits, and pulp and paper prices. Whereas from the supply side, the most critical variables are the relative wages with the competitive sectors. Therefore, a pairwise directional analysis may not provide a complete picture of the drivers of employment. To bridge the gap, we apply the directed acyclic graph (DAG) method and variance decomposition of forecast errors (VD) to analyze contemporaneous and long-term causal relationships between employment, wages, mechanization, logging product prices, and production levels in the logging industry.

This article is organized as follows. The next section introduces the data and describes the empirical approach adopted. Following that, we present the empirical results, with policy implications in the final section.

Data and Empirical Approach

Data sources

We extracted the data for the logging industry (Code 1133, North American Industrial Classification System; Instituto Nacional de Estadística y Geografía (INEGI) of Mexico, Statistics Canada, and the United States Office of Management and Budget 2017) from quarterly workforce indicators (US Census Bureau 2021), timber product output (TPO) reports (USDA Forest Service 2021), wood supply chain analysis (Barynin et al. 2013), and TimberMart-South (Norris Foundation 2021b) to construct the time-series dataset used in this study (Table 1). Due to the limited availability of data, we work on a smaller dataset from 11 states (Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia) for 11 years, from 2007 to 2017. There were a few missing data in the TPO dataset in 2008, 2010, 2012, 2014, and 2016. As a result, we applied the average interpolation method for the missing data between two data

Table 1.—List of variables.

Variable (unit)	Description	Data Sources[a]
Emp (No.)	Employment in the logging industry	US Census Bureau QWI
W ($)	Average monthly earnings of logging workers	US Census Bureau QWI
K ($/green short ton)	Capital stock per ton of production	WSRI wood supply chain analysis
P ($/MBF)	The delivered price of logging product	TimberMart-South, Quarterly Timber Prices Report 1977–2021
Q (1000 cubic feet)	Logging production level	USDA Forest Service TPO

[a] QWI = quarterly workforce indicators; WSRI = Wood Supply Research Institute; MBF = 1,000 board feet; TPO = timber product output.

points. The average interpolation method is one of the simplest and most applicable methods for imputing the missing economic data without changing the overall variable average (Saeipourdizaj et al. 2021). Table 1 shows the list of variables used in this study. To reduce the skewness of the raw data, the *Emp*, *W*, and *Q* were transformed into their respective logarithmic forms.

Empirical approach

The following steps were used to investigate the causal relationships between employment, wage, mechanization, product prices, and production level in the logging industry. First, a multivariate time-series model, the vector autoregression (VAR) model, was applied. Next, a graphical modeling analysis, the directed acyclic graph (DAG) approach, was used to capture the dynamic relationships between variables and determine their contemporaneous causal relationships. Finally, a structural analysis, forecast error variance decomposition (VD), was conducted to identify how the shocks change over time.

Vector autoregression.—The vector autoregression (VAR) model was first proposed by Sims (1980), in which a framework for understanding the causal relationships of multivariate time-series data is provided. This article used the VAR model to capture the dynamic interdependence between employment, wage, mechanization, logging product price, and logging production level. The VAR model with n variables can be written as:

$$Y_t = c + \sum_{l=1}^{p} B_l Y_{t-l} + \varepsilon_t \qquad (1)$$

where Y_t is an $(n \times 1)$ vector of the intended variable; c is an $(n \times 1)$ vector of constants; p represents the lag order of the model; B_l is an $(n \times n)$ matrix of autoregressive coefficients to be estimated for lagged l period; ε_t is an $(n \times 1)$ vector of uncorrected random errors. In this study, Y_t is a (5×1) vector including the variables *Emp*, *W*, *P*, *Q,* and *K* in period t; c is a (5×1) vector; B_l is a (5×5) matrix of coefficients; and ε_t is a (5×1) vector.

However, the VAR model cannot explain the contemporaneous relationships between the variables because the correlation is hidden in the error term of the VAR model (Haigh and Bessler 2004, Ji et al. 2018). Additionally, it is hard to economically explain the coefficients of the VAR model (Sims 1980). As a result, directed acyclic graph and forecast error variance decomposition were widely used based on the VAR model.

Directed acyclic graphs.—The DAG approach was pioneered by Pearl (1995) and Spirtes et al. (2000) to explore the contemporaneous causal relationships and identify the causal patterns. The DAG approach was first used to determine the causal flows based on the residual of the VAR model by Swanson and Granger (1997). The residual correlation coefficient of the VAR model can be applied to build upon the contemporaneous causal flows by the DAG approach. In this article, we used the DAG approach to explore the contemporaneous relationships of economic factors in the logging industry and identify the causal patterns among them.

The basic idea behind the DAG is to depict the causal link (cause → effect) between two variables to represent the contemporaneous causal flow. If these two variables, for example, X and Y, are linked by an arrow, it signifies they are adjacent. The arrow represents the causal relationship between X and Y. If the arrow is from X to Y ($X \rightarrow Y$), X is referred to as the parent of Y, and Y is X's child (Chen et al. 2021), which suggests X results in Y. Therefore, if there is no edge between X and Y ($X\ Y$), it means there is no causal relationship between X and Y. If there is a nondirected edge (X–Y), it means the direction of the causal relationship between X and Y is unknown. Also, the bidirected edges ($X \leftrightarrow Y$) indicate a bidirectional causality relationship between X and Y (Pan et al. 2019). However, the bidirectional edges do not exist in DAG (Chen et al. 2021).

In this study, we applied the Peter–Clark (PC) algorithm to identify the edges and direction of the causal relationship among the variables. The PC algorithm is divided into two steps:

First, a complete undirected graph is built up. In this graph, all the variables have an edge linking to every other variable. Then, the unconditional correlation test between any pairs of variables is carried out. If the correlation is not statistically different from zero, the edge between these two variables would be eliminated.

Second, conditional correlation is tested for the remaining edges. The remaining edges are checked for the first-order conditional correlation, given any third variable. The edge will be deleted if the correlation is not statistically different from zero. Then the edges that survive the first-order conditional correlation test are checked for second-order partial correlation, and so on. The algorithm continues to check the conditional correlation test for N variables until $(N-2)$th order (Spirtes et al. 2000).

To test whether the unconditional correlations and conditional correlations are statistically different from zero, Fisher's z statistic was applied in this study:

$$z[\rho(i,j|\ k)n] = \left[\frac{1}{2}\sqrt{n-|k|-3}\right] \times \ln\left\{\frac{|1+\rho(i,j|\ k)|}{|1-\rho(i,j|\ k)|}\right\} \qquad (2)$$

where n is the number of observations that are applied to calculate the correlations, $\rho(i,\ j|k)$ is the population conditional correlation coefficient between series i and j, which is conditional on series k (Bessler and Yang 2003).

Forecast error variance decomposition.—To analyze the dynamic structure of the VAR model, we apply the forecast error variance decomposition (VD) method to simulate how much of the forecast error variance of employment, wage, mechanization, production level, and product price can be explained by exogenous shocks to the other variables and endogenous shocks by themselves (Bernanke and Gertler 1995).

A VAR can also be expressed as a vector moving average model (VMA; Enders 2008). Therefore, Equation 1 can be iterated backward infinite times to obtain a moving average order:

$$Y_t = \mu + \sum_{l=0}^{\infty} B_l \varepsilon_{t-l} \tag{3}$$

where Y_t is an $(n \times 1)$ vector of the intended variable; $\mu = (I + B_1 + B_2 + B_3 + \ldots)B_0$ is an unconditional mean of Y_t (Sheng and Tu 2000, Alsaedi and Tularam 2020).

Thus, the mth horizon forecast error is

$$Y_{t+m} - E_t(Y_{t+m}) = \sum_{l=0}^{m-1} B_l \varepsilon_{t+m-l} \tag{4}$$

And the mth horizon forecast error variance of $y_{1,t}$ is

$$\mathrm{var}(y_{1,t+m}) = \varepsilon_1^2 \sum_{l=1}^{m-1} \theta_{1,2}^2(l) + \varepsilon_2^2 \sum_{l=1}^{m-1} \theta_{1,3}^2(l) + \ldots + \varepsilon_n^2 \sum_{l=1}^{m-1} \theta_{1,n}^2(l) \tag{5}$$

where θ is the impulse response function. Therefore, the ratio of relative variance contribution can be represented as:

$$R_{1,n}(m) = \frac{\varepsilon_n^2 \sum_{l=1}^{m-1} \theta_{1,n}^2(l)}{\mathrm{var}(y_{1,t+m})} \tag{6}$$

where $R_{1,n}$ (m) represents how much of the change in variable 1 is caused by the shock of variable n at the mth horizon (Enders 2008).

Because of the contemporaneous correlation among the errors of the VAR model, Cholesky decomposition is used to orthogonalize the covariance matrix of the residuals (Sims 1980). However, the input order of the variable would be essential to the VD (Swanson and Granger 1997) because different input order leads to varying results of VD. The previous research confirms the input order based on their subjective causal assumptions and analyses (Omisakin 2008, McKenzie et al. 2009, Alsaedi and Tularam 2020, Esmaeili and Rafei 2021). The DAG approach identifies the causal patterns based on the data without any subjective assumptions and analyses, which can be used to confirm the input order of VD.

Due to the panel structure of the dataset, it is necessary to test the stationarity of each panel series to avoid spurious regression and ensure the validity of the results. Harris–Tzavalis (1991), Breitung (2002), and Phillips–Perron–Fisher tests (Maddala and Wu 1999) were applied to examine whether the dataset shows stationarity. If all variables were not stationary at their level, the Johansen–Fisher panel cointegration test was performed on the dataset. The Johansen–Fisher test is a nonparametric test that does not assume homogeneity in the coefficients (Maddala and Wu 1999). After testing the stationarity and cointegration of our data, a VAR model of employment and the influencing factors were established. Subsequently, the DAG approach was applied to identify the causal relationship among the variables based on the results of the VAR model. Finally, the VD was used to investigate the dynamic relationship among the variables in the long run.

Results

The preceding section discusses the analysis results for DAG and VD. The DAG section is subdivided to focus on each of the paths among employment, production level, wage, capital, and product price. The VD section focuses on the dynamic relationship among these variables in the long run (Table 2). The tools used for performing the aforementioned analyses are included in the Appendix. Table 3 presents the panel data unit root test, Table 4 showcases the panel data cointegration test, followed by the vector autoregression (VAR) in Table 5.

Directed acyclic graph results

After testing the stationarity and cointegration of each panel series, we found that all variables are not stationary at

Table 2.—Results of forecast error variance decomposition (VD).

VD of Variable	Year	*P*	*W*	*Emp*	*K*	*Q*
P	1	1.000	0.000	0.000	0.000	0.000
	2	0.925	0.002	0.006	0.038	0.030
	3	0.841	0.002	0.010	0.100	0.046
	4	0.777	0.001	0.011	0.163	0.048
	5	0.734	0.001	0.011	0.212	0.043
	10	0.682	0.001	0.007	0.283	0.027
W	1	0.313	0.687	0.000	0.000	0.000
	2	0.335	0.640	0.004	0.017	0.004
	3	0.387	0.541	0.009	0.054	0.009
	4	0.461	0.406	0.013	0.107	0.014
	5	0.538	0.266	0.015	0.163	0.018
	10	0.677	0.011	0.009	0.278	0.026
Emp	1	0.005	0.013	0.982	0.000	0.000
	2	0.051	0.031	0.895	0.003	0.019
	3	0.124	0.041	0.780	0.003	0.053
	4	0.200	0.042	0.672	0.003	0.084
	5	0.280	0.038	0.568	0.008	0.106
	10	0.642	0.005	0.090	0.201	0.062
K	1	0.126	0.001	0.013	0.860	0.000
	2	0.399	0.000	0.007	0.594	0.000
	3	0.550	0.001	0.005	0.44	0.004
	4	0.621	0.001	0.005	0.363	0.01
	5	0.653	0.001	0.006	0.325	0.015
	10	0.680	0.001	0.007	0.288	0.025
Q	1	0.522	0.007	0.002	0.100	0.370
	2	0.648	0.031	0.013	0.156	0.152
	3	0.682	0.031	0.018	0.197	0.071
	4	0.689	0.022	0.018	0.226	0.045
	5	0.688	0.014	0.016	0.246	0.036
	10	0.682	0.001	0.008	0.282	0.027

Table 3.—Results of panel unit root test.

Variables	Method[a,b] H-T	Breitung	PP–Fisher
Level			
Emp	0.999	0.329	100.584***
W	1.006	−0.125	12.750
P	0.971	1.226	142.927***
Q	0.999	−0.582	29.581
K	1.022	1.814	78.654***
First difference			
Emp	0.393***	−2.473***	50.758***
W	−0.413***	−3.985***	188.699***
P	0.133***	−3.550***	67.822***
Q	0.483***	−1.531*	31.323*
K	0.412***	−2.065**	34.505**

[a] H-T = Harris–Tzavalis; PP–Fisher = Phillips–Perron–Fisher.
[b] ***, **, and * denote rejection of the null hypothesis at the 1%, 5%, and 10% levels, respectively. The lag length for stationarity tests is automatically selected by statistical software, Stata (Herwartz et al. 2018), based on Schwarz information criterion (Hadri 2000).

their level but integrated under order one and have a long-run stable equilibrium relationship. Hence, we carried out a VAR model and got the residual correlation coefficient matrix of the VAR model. Following that, we applied the PC algorithm in Tetrad 6.8 to analyze the residual correlation coefficient matrix to obtain the DAG. The DAG, in turn, was used to disclose the contemporaneous causal structure.

In Figure 2, the complete undirected graph shows the undirected path connecting each variable with every other variable. It reveals that these five economic variables were interrelated with each other.

Figure 3 presents the DAG on these variables at the 20 percent significance level, which allows us to more accurately identify a contemporaneous causal relationship in a small sample (Spirtes et al. 2000). It shows the causal relationship paths among employment, production level, wage, capital, and product price, indicating that these five factors are interconnected in contemporaneous time. There are seven paths in the graph: $P \rightarrow W$, $P \rightarrow Emp$, $W \rightarrow Emp$, $Emp \rightarrow K$, $Emp \rightarrow Q$, $W \rightarrow K$, and $K \rightarrow Q$.

The contemporaneous causal relationship between employment and its influencing factors can be refined into the following two paths: $P \rightarrow Emp$ and $P \rightarrow W \rightarrow Emp$.

- $P \rightarrow Emp$: The results show that there is no causal link toward product price. In other words, the product price is not driven by any other factors, suggesting the price is exogenous in contemporaneous time. The product price can directly affect employment.

Table 4.—Results of panel cointegration test.[a,b]

Method[a]	Pedroni Test		Kao Test		Westerlund Test
Modified PP	4.218***	ADF	−2.130**	Variance Ratio	2.850***
PP	−4.128***				
ADF	−5.814***				

[a] PP = Phillips–Perron; ADF = augmented Dickey–Fuller.
[b] ***, **, denote rejection of the null hypothesis at the 1% and 5% levels, respectively.

Table 5.—Residual correlation coefficient matrix of VAR.

	Emp	*W*	*P*	*Q*	*K*
Emp	1.0000				
W	0.9723	1.0000			
P	−0.5403	−0.4526	1.0000		
Q	−0.9733	−0.9787	0.4953	1.0000	
K	0.9766	0.9896	−0.4797	−0.9876	1.0000

- $P \rightarrow W \rightarrow Emp$: The DAG algorithm shows that product price causes changes in wage, and wage directly impacts employment, indicating that the product price has an impact on employment directly and indirectly in the immediate short term.

Figure 3 also shows the contemporaneous relationship between employment, wage, capital, and production level, which is discussed here further:

- $Emp \rightarrow K$: Employment affects capital in contemporaneous time.
- $Emp \rightarrow Q$: Employment also has an influence on the production level.
- $W \rightarrow K$: The wage has a direct effect on capital in the immediate short term. Both wage and employment are the contemporaneous causes of capital, and the price affects capital indirectly through employment and wage.
- $K \rightarrow Q$: The production level is found to be affected by capital.

Forecast error variance decomposition results

After analyzing the contemporaneous causal relationship via DAG, we then investigated how much of the change in employment across time is caused by endogenous shocks by itself and how much is caused by exogenous shocks as well as other variables. The VD was used to investigate this dynamic relationship among variables (Table 2).

Table 2 reports the decomposition at horizons 1, 5, and 10 years. It shows that employment in the logging industry is most prominently explained by itself in the first year at 98.2 percent. The influence from employment itself is then reduced to 56.8 percent at the 5-year horizon and 9.0 percent at the 10-year horizon. Product prices and wages come in the second and third positions, respectively. The influence of the product price on employment gradually increases over time, and the percentage contribution rises from 0.5 percent at the 1-year horizon to 28.0 percent at the 5-year horizon and 64.2 percent at the 10-year horizon. Capital has an increasing influence on employment over time, and the percentage contribution increases from 0 percent at the 1-year horizon to 20.1 percent at the 10-year horizon. The wage and production level have a slight influence on employment over time.

The forecast error variance for the wage is most prominently explained by the endogenous shock of wage itself (68.7%), followed by the shock of the product price (31.3%) at the 1-year horizon. The shocks from employment, capital, and production are small compared to that of product price and wage itself, which are consistent with those of the DAG. In addition, the forecast error variance for capital is most prominently explained by itself and product price. Production level is most prominently explained by itself and product price and capital.

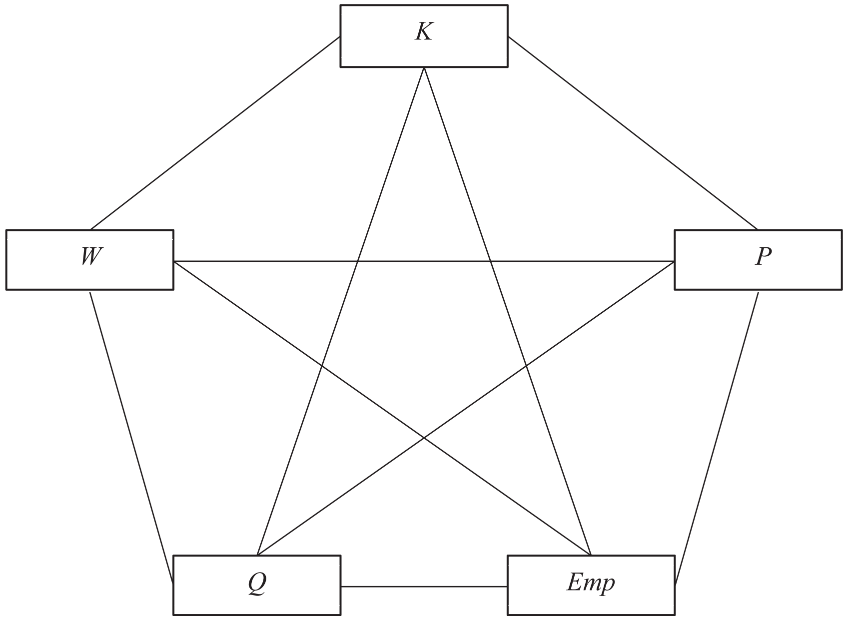

Figure 2.—Complete undirected graph on employment in the logging industry.

Discussion

Directed acyclic graph analysis

P → Emp *and* P → W → Emp.—The product price is an important signal for the logging firms. As price takers, when the logging product price decreases, the logging firms have to reduce their costs. Faced with falling prices in a highly competitive and homogeneous industry like logging, the firms are more likely to reduce costs by reducing labor costs instead of nonlabor costs (Bertola et al. 2012). Therefore, laying off employees and reducing the wage would be the preferred adjustment strategy.

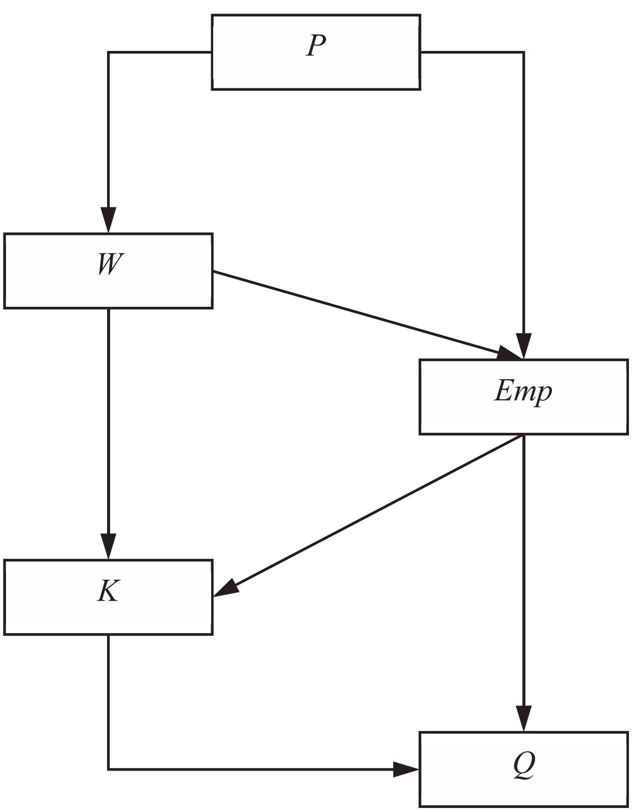

Figure 3.—Directed acyclic graph on employment in logging industry (significant level at 20%).

The logging product price is highly dependent on the business cycle (He et al. 2022). With the decrease in new housing units started during the economic downturn, as well as the decreasing demand for house renovation and furniture, the logging product price decreased (Xiang and Yin 2006, Drapala 2009). For example, the economic prosperity fostered more than two million housing starts in 2005 and then promoted the logging product price in 2005 (Keegan et al. 2011). However, the price of logging products decreased dramatically during the recession in 2008 because of the sharp decline in demand for wood-frame housing and a systematic reduction in the pulp and paper and furniture industries (Grushecky et al. 2006, Abbas et al. 2014), whose production fell by 75 percent between 2005 and 2009 (Hodges et al. 2011).

Thus, the logging firms lay off workers to minimize operating costs in response to falling prices. The reason why logging firms can lay off workers easily may be that logging workers do not have long-term employment contracts, or they are not the permanent employees. Seasonal operation is one of the important reasons for short-term contracts or temporary employment. For example, logging firms in the South are partially shut down in the third quarter while operating for the rest of the year (Bureau of Labor Statistics 2022). The North has always faced seasonal challenges because of spring thaw (Conrad et al. 2018). Paid logging workers in hourly, daily, or weekly and hiring undocumented foreign workers are also causes for the lack of long-term employment contracts (Bertola et al. 2012, He et al. 2021). Another reason why logging firms can lay off workers easily may be that the logging industry was not unionized (Neumann 2019). Thus, the logging workers have had no power to negotiate with the employers. Further, there was a closure wave among the mills and logging firms, even though some were not permanent closures, due to the severe market conditions (Keegan et al. 2011, Wilson 2017).

As a result, when logging product prices decreased during the recession in 2008, logging employment in 2010 fell by 22.3 percent from 2005 (US Census Bureau 2021). When the economy is prosperous, the increasing demand for logging production stimulates the price (Yin 2001). The logging firms would recruit more employees and in turn expand production.

Logging product price also has an impact on the wages of logging workers. According to classical economics, facing lower prices, firms would decrease the nominal wages, resulting in lower real wages, increasing or, at least, maintaining some profits (Bertola et al. 2012). For example, between 2007 and 2009, the real price of logging products among Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Texas, and Virginia fell by 16.9 percent, while the real wages dropped by 3.5 percent (Norris Foundation 2021a, US Census Bureau 2021), and the real profits per firm in some major forest states in 2009 were estimated to be 20.3 percent lower than those in 2007 (He et al. 2021). The reason why the wage decreased less than that of the price might be the wage rigidity. Logging firms are more likely to reduce employment than lowering wages because firms are constrained by the contracts signed at higher bargaining levels (Kahn 1997, Lebow et al. 2003). Thus, the logging firms would react to logging product price shocks by reducing employment first, especially temporary employment, then by cutting pay (Bertola et al. 2012).

In addition, wages can provide market signals for logging firms and workers. During economic recovery and expansion, the logging product price would increase, and the logging firms would raise wages to recruit more employees. The logging firms may offer more decent wages to provide incentives for the existing employees to work longer hours and to match the higher production level. Some firms may offer higher wages to hire trained employees to increase productivity. In the context of expected experience, the wage increase by the proficiency level of the workers is reasonable (Xu et al. 2014). The higher wages also signal opportunities and career prospects, attracting additional employees. When the American economy was recovering in 2010, the real price increased by 2.7 percent, while the real wage and employment increased by 4.9 and 1.2 percent, respectively (Norris Foundation 2021a, US Census Bureau 2021).

Emp → Q *and* Emp → K.—In response to price changes, logging firms are more likely to adjust production levels by adjusting employment. For example, during the recession in 2008, due to the severe market conditions, logging firms laid off workers to minimize the operating costs and then reduce production. In most major logging states, such as most southern states, logging employment has declined to various degrees (Fig. 1), thereby lowering the amount of timber harvested (USDA Forest Service 2021).

Employment also has a direct effect on capital. On the one hand, reduced employment can lead to an increase in capital. The US logging industry faces some severe situations, such as an aging workforce and declining recruitment of the upcoming generations (He et al. 2021). As more and more employees retire, recruiting new employees is challenging for low profit margins and is full of uncertainty, instability, and seasonal operations (Egan and Taggart 2009, Shivan et al. 2020). Logging is physically demanding and a hazardous civilian occupation in the United States because logging workers must spend all their time outdoors, sometimes in poor weather, and often in isolated areas (Scott et al. 2020, Bureau of Labor Statistics 2020b). However, logging firms cannot offer attractive salaries to attract new employees (He et al. 2021), especially younger workers to replace retirees (Baker and Greene 2008). Thus, the logging firms have to replace jobs by substituting mechanized harvesting systems for workers, which means that the decrease in employment has an impact on the increasing capital.

On the other hand, increased employment can result in a decrease in capital. The logging firms, especially small-scale firms, tend to employ more staff to minimize costs instead of investing in mechanized systems. Small-scale logging firms have been remarkably tenacious. They are developed with a long history and are widespread in the United States (Conrad et al. 2018). One of the main reasons for the presence of many small logging firms is parcelization (Yin et al. 1998, Milauskas and Wang 2006). The number of forestland owners has increased rapidly in the last decade, resulting in a decline in the average size of forest ownerships, most of which are nonindustrial private forest (NIPF) owners (Rickenbach and Steele 2006). However, the large logging firms with mechanized harvesting systems may not match this small-scale forestland as well as the low logging volume (Greene et al. 1998). In contrast, small logging firms have advantages in harvesting on small-scale forestland (Blinn et al. 2015). Unlike large firms, small logging firms do not own mechanized equipment and employ more staff to minimize costs (Shivan et al. 2020). Compared with large firms, small-scale firms are more inclined to operate seasonally and reduce capital expenses to maintain efficiency. They are also less likely to afford the cost of equipment repair and maintenance (LeBel and Stuart 1998). As a result, small logging firms are ''hand crews,'' hiring employees to harvest timber by chain saw instead of mechanized harvesting systems (Egan 2011).

W → K → Q.—Wages have a direct effect on capital, too. Obviously, high wages can provide incentives for logging firms to replace labor with machines. However, they also possibly have made the replacement harder and slower. It was estimated that initial investments in mechanized harvesting systems were around $0.4 to $1.5 million, and monthly finance payments were around $5,000 to $20,000 (Rickenbach and Steele 2005). Logging firms must remain profitable to remain in business and continue investing in their businesses, but the high wage reduces their profitability because the most considerable contribution to costs is wages (Jacobson et al. 2009). In the South, the wages account for an average of about 30 percent of the total costs (Xu et al. 2014). As a result, confronting high wages, logging firms, especially small logging firms, cannot afford the wage costs of large teams or investment in mechanized systems, instead, they would outsource some production processes instead of investing in mechanized systems, which can cope with the low production level (Stuart et al. 2010). Logging firms tend to contract labor-intensive activities because they can alleviate their workload and keep a small staff crew (Wang 1999), thus saving of salary costs. For example, trucking is a significant cost for logging firms (Yin and Caulfield 2002), and most small firms cannot afford substantial investments and expenses of trucking, so they would choose to contract out trucking, which can be much cheaper than operating their fleets, and focus on the harvesting business (Hamsley et al. 2007, Shivan et al. 2020).

In addition, logging firms can benefit from mechanization by using more equipment and technology to promote production levels (Mac Donagh et al. 2017). In the past two decades, logging firms have promoted the mechanization of harvesting systems. The proportion of loggers using the capital-intensive mechanized harvesting systems has increased over time, making logging a much more capital-intensive industry (Kollberg 2005).

The mechanization process enables logging firms to attain higher productivity. The productivity of logging firms in most states has increased since 1997 because of the widespread use of mechanized harvesting systems (He et al. 2021). The mechanized firms in Wisconsin produced an average of 0.73 million cubic feet yearly, while the nonmechanized firms produced only 0.23 million cubic feet yearly (Rickenbach and Steele 2005). Previous research shows that due to significant capital investments, production increased from 3.4 to 5.5 tons per person-hour between 1987 and 2012 in the South (Greene et al. 2013). In particular, the weekly production level per firm in Georgia has increased by 83 percent since 1987 because of mechanization (Baker and Greene 2008). Therefore, the mechanized harvesting systems contributed to increasing production level (Cubbage and Carter 1994).

Forecast error variance decomposition analysis

As shown in Table 2, the change in employment in the logging industry is most prominently explained by the endogenous shock of employment itself in the first five years. One reason for that might be the employment stickiness. The logging firms would consider the cost of employment adjustment and the indivisibility of employment when they tried to adjust the employment in the long run (Vermeulen 2006).

Unlike in the contemporaneous time, on one hand, the VD shows that the capital has an increasing influence on employment in the long run. The logging industry is more and more capital intense. In the sample states, the capital increased from \$16.5/green short ton in 2007 to \$21.3/green short ton in 2017. A drastic reduction in employment occurred between 2007 and 2009, from 30.3 thousand to 26.3 thousand, and employment was 26.4 thousand in 2017, not recovering to historical levels in 2007. Further, the production level was 8.1 million MCF in 2007, then dropped to 6.7 million MCF in 2009, and recovered to 8.2 million MCF in 2017. According to these data, the production level has recovered with the capital increase; however, the employment still kept at a low level. Thus, this indicates that capital substitutes for labor in the long run. The productivity of the mechanized harvesting systems is much higher than the manual systems, and thus the logging industry now has far more capacity than demand. The capacity utilization of logging firms with mechanized harvesting systems was only 70 to 84 percent on average (Conrad et al. 2017, 2018). Therefore, the demand for logging workers decreased because of the increased productivity caused by mechanization. Specifically, the mechanized harvesting systems are displacing the chainsaw fallers (Conrad et al. 2018). The employment of logging equipment operators had remained stable, from 22,130 in 2007 to 21,290 in 2017, while the employment of chainsaw fallers declined substantially, from 6,380 in 2007 to 3,880 in 2017 (Bureau of Labor Statistics 2020a), indicating that capital leads to a reduction in employment in the long run.

On the other hand, employment plays a decreasing role in driving capital with the extension of the forecast period. This result may be explained by the fact that the logging firms need to consider costs, markets, profitability, and ease of obtaining loans to decide whether to purchase machines in the long run or not. Therefore, the impact of employment on capital, in the long run, will be reduced.

As shown in Table 2, the wages have a small influence on capital in the long run. This result might be explained by the fact that wage increases have been long term and stable in promoting logging firms to choose to outsource some of their businesses instead of mechanization. In general, mechanized harvesting systems require tremendous investment.

It is acknowledged that employment is influenced by capital and the product price. However, the product price is determined merely by itself in the long run, which is consistent with results of the DAG. This feature may partly be explained by price rigidities, such as menu costs and other frictions in adjusting prices (Angeletos and La'O 2009) or imperfect information (Lucas 1972, Mankiw and Reis 2002).

Conclusions

This study investigates the driving factors for employment in the logging industry in the United States from 2007 to 2017. A DAG approach was applied to study the contemporaneous causal relations among employment, wage, mechanization, product prices, and production level. The VD was then used to analyze the dynamic relationship among variables in the long run.

The DAG analysis results show that two conduct paths affect employment in the logging industry. First, the product price directly affects employment. Second, the product price drives wages, and wages promote employment. In addition, employment has an effect on mechanization and production level. However, wages affects mechanization, followed by the influence of mechanization on the production level. The VD results based on the DAG and VAR model verify that employment is most prominently explained by itself, the product price, and wages. Unlike the contemporaneous time, the VD shows that mechanization has an increasing long-term effect on employment. This finding that mechanization substitutes for workers in the logging industry in the long run is consistent with other studies (Abt 2013, Conrad et al. 2018, He et al. 2021).

We put third the following policy implications and suggestions based on the previous empirical results. First, if the policy goal is to promote employment and maintain employment stability, then increasing logging production supplies from small-scale logging firms would be helpful because they are more inclined to hire employees to reinforce the competitive position of large firms rather than mechanization. Lee and Eckert (2002) have also made a broadly similar point. Second, although mechanization can solve the shortage of employment and increase production levels, many logging firms still hire employees instead of purchasing machines because several conditions need to be considered to achieve mechanization: low loan interest, ease of obtaining loans, efficient equipment maintenance, reasonable operating costs, and production level compatible with mechanized harvesting systems (Mac Donagh et al. 2017, Cook et al. 2021, He et al. 2021). As a result, if the policy goal is to promote the mechanization of the logging industry, or increase the production level of logging products, then policymakers at least need to address these obstacles: providing tax breaks, loan concessions, and fiscal subsidies for those firms which are going to purchase mechanized harvesting systems. Third, with the advancement of mechanization, the logging workers also need to keep up with technological progress. The policymakers can offer some skills training programs to increase the number of qualified logging machine operators, for example, assisting in the transformation from ''hand crews'' into mechanized crews.

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Appendix

Panel data unit root test

For time-series data analysis, it is required to confirm the stationarity of the data series and avoid the potential spuriousness (Kao 1999, Olagunju et al. 2021). As a result, applying the panel unit root test is necessary before analyzing the panel data (Table 3). In our study, the Harris–Tzavalis (Harris and Tzavalis 1999), Breitung (Breitung 2002), and PP–Fisher (Maddala and Wu 1999) tests were explicitly used. Specifically, the lag length for stationarity tests is automatically selected by statistical software, Stata (Herwartz et al. 2018), based on Schwarz information criterion (Hadri 2000).

The results show that none of the level tests on the W and Q rejected the null hypothesis of nonstationarity or existence of a unit root, but all the first-difference tests on them rejected the original hypothesis; these results indicate that the W and Q are first-difference stationary and integrated of order one, I(1). Only the level test of the PP–Fisher on *Emp*, P, and K rejected the null hypothesis and not the Harris–Tzavalis and Breitung tests. However, all of the first-difference tests on them significantly rejected the null hypothesis. Therefore, *Emp*, P, and K can be regarded as first-difference stationary and integrated of order one, I(1).

Panel data cointegration test

Because all variables are not stationary at their level but integrated under order one, it is necessary to use the panel cointegration test before further econometric analysis. To make sure the results are robust, the Pedroni (Pedroni 2004), Kao (McCoskey and Kao 1998), and Westerlund (Westerlund 2005) tests were applied (Table 4). The results show that all the cointegration tests significantly reject the null hypothesis (no cointegration). Hence, strong evidence indicates that all five variables have a long-run stable equilibrium relationship. Therefore, all variables at the level are used in the empirical analysis, as no differences are needed.

Vector autoregression

After testing the stationarity and cointegration of our data, a VAR model of employment and the influencing factors was set up. Table 5 shows the results of the five-variable VAR residual correlation matrix. The DAG approach was applied to analyze these five variables' VAR residual correlation matrix to get contemporaneous causal patterns among employment, wage, capital, product price, and production level.