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Price Discovery and Integration in U.S. Peanut Markets

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Abstract

The United States is a major supplier in the world peanut market. Using grower-level monthly peanut price data from 1982 to 2018, we estimate market integration and price discovery patterns at the grower level by applying causality structures identified through machine-learning algorithms. Preliminary analysis shows that Georgia is a price leader and others are followers in current and lag time. Peanut prices in Texas and Georgia are important determinants of prices in other markets such as North Carolina, Virginia, and Alabama. Findings from this study are useful for peanut producers, marketers, and policy makers designing peanut marketing programs.

Keywords: directed acyclic graphs, machine learning, market integration, peanut prices, price discovery

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Introduction

The United States is a significant supplier in the world peanut market.[1] In the United States, 99% of peanuts are grown in ten states. Georgia grows about 50% of U.S. peanuts, followed by Texas (10%), Alabama (10%), Florida (9%), South and North Carolina (14%), Mississippi, Virginia, New Mexico, and Oklahoma (American Peanut Council, 2018). According to the National Agricultural Statistical Service (NASS) of the U.S. Department of Agriculture (USDA), peanut producers received a national average farm-gate price of $0.23/lb in June 2018 (U.S. Department of Agriculture, 2018). In the United States, peanut prices vary by state. As a result, it is likely that peanut price discovered in one state may affect the price-discovery process of another state, given the proximity of peanut-producing states. Information about peanut-market integration and price discovery patterns, if any, would be useful not only for U.S. peanut producers but also for marketing and promotion groups such as the National Peanut Board.

The U.S. peanut market has an annual market value of over $1 billion, with a significant economic impact on the 10 southern states that produce the majority of U.S. peanuts. Many factors, including production regions of various peanut types, agricultural policies, and the global market, are important for understanding the peanut market and price relationships among states.

Four main varieties of peanuts are grown in the United States: Runner, Virginia, Spanish, and Valencia (American Peanut Council, 2018). Runners (80% of U.S. production), which are mainly used for peanut butter, are grown in Georgia, Alabama, Florida, Texas, and Oklahoma. Sold salted or roasted, Virginia-type peanuts (15% of U.S. production) are grown in southeastern Virginia, northeastern North Carolina, South Carolina, and west Texas. Oklahoma and Texas are responsible for most of the production of Spanish-type peanuts (4% of U.S. production), which are primarily sold in candy, salted, and as peanut butter. Valencia-type (less than 1% of U.S. production) are mainly grown in New Mexico; these are roasted and sold in the shell or used for boiled peanuts. Peanuts for edible use account for the majority of peanut consumption in the United States; other uses include peanut oil, seed, and feed (U.S. Customs and Border Protection. 2008).

Until 2002, peanuts were sold under a marketing quota system that guaranteed producers with quota rights a high price on a "government-established 'quota loan rate' of $610 per ton (during 1996–2001)" (Dohlman et al., 2004, p. 3). Producers without quota rights exported their peanuts at world prices, which were much lower than the quota loan rate prices. Import restrictions were also a component of the marketing quota system, but the North American Free Trade Agreement (NAFTA) and World Trade Organization (WTO) agreements opened the peanut market through tariff rate quotas. These trade agreements, and opposition from consumer groups and peanut processors, contributed to the demise of the marketing quota system (Dohlman et al., 2004). The 2002 Farm Act ended the marketing quota system and allowed peanut producers to receive marketing assistance loans, fixed direct payments, and counter-cyclical payments, forms of government assistance that had been available to grain, oilseed, and cotton producers.

[1] China and India are the largest suppliers of peanuts worldwide. Other major producers include Senegal, Sudan, Brazil, Argentina, South Africa, Malawi, and Nigeria (Virginia Carolinas Peanuts, 2018).

Following the passage of the 2002 Farm Act, farm-level prices and total U.S. peanut plantings decreased. Major peanut-producing states in the southeast, such as Georgia and Florida, experienced stable or increased planted acreage, but other states—particularly Virginia, Texas, and Oklahoma—saw large decreases in planted acreage (Dohlman et al.. 2004). Despite these changes, changes in prices, market promotion, and dietary preferences contributed to a record 9% increase in U.S. peanut consumption over 2003–2004 (Dohlman et al., 2004). Bolotova (2018) found that yearly average area harvested decreased 13% from 2002 to 2016, yearly average yield increased 37%, and yearly average peanut price decreased 22% compared to 1980–2001.

Following the end of the marketing quota system, peanut producers managed risk by "increasing their use of marketing contracts to lock in prices and by maintaining a diversified commodity mix to spread risk" (Dohlman, Foreman, and Da Pra, 2009). Non-quota holders had primarily used marketing contracts prior to the policy change; with the end of the quota program, the percentage of producers using marketing contracts rose from 40% in 2002 to 65% in 2007 (Dohlman et al., 2004). The end of the quota system resulted in producers having less of a bargaining position with shellers. Without the minimum support price that had been set under the quota system, shellers were no longer willing to "contract at the support price" (Smith and Wolfe, 2004, p. 2). According to Adjemian, Saitone, and Sexton (2016, p. 586), "The typical contract has a one-year term, and processors make take-it-or-leave-it offers to farmers for a price equal to the US Department of Agriculture (USDA), Commodity Credit Corporation's (CCC) loan rate plus a premium."

In addition, the peanut market is relatively thin, with no futures or cash market; only two companies process 70% of U.S. peanuts (Adjemian, Saitione, and Sexton, 2016): Birdsong Peanuts and Golden Peanut Company each operate six peanut-processing facilities and over 80 buying points throughout the U.S. peanut-growing region. Ultimately, the end of the marketing quota system had a profound effect on how prices were determined. In this light, the general objective of this study is to discover market integration and price discovery patterns in major peanut producing states in the United States. Specific objectives are to determine: (i) patterns in grower-level peanut prices from 1982 through 2018 in major peanut-producing states in the United States before and after the discontinuation of the price quota system and (ii) peanut market integration and price discovery patterns across the states using machine-learning algorithms (such as directed acyclic graphs) for before and after the discontinuation of the price quota system.

Data

Data used in this study are from the USDA National Agricultural Statistics Service (NASS). These data consist of the monthly price received, measured in dollars per pounds, for six states from 1982 through 2018. These states consisted of Georgia, Alabama, Texas, Florida, North Carolina, and Virginia. Other peanut-producing states (e.g., Arkansas, Mississippi, New Mexico, South Carolina, and Oklahoma) were not considered in the study due to inconsistencies in price data. Table 1 reports summary statistics for the data.

The end of the quota system in 2002 drastically changed the peanut market and how prices were determined. Due to this difference, we split the data into two periods: 1982–2001 and 2002–2018.

Table 1. Summary Statistics: Monthly Peanut Prices, $/lb

	AL1	AL2	FL1	FL2	GA1	GA2	NC1	NC2	TX1	TX2	VA1	VA2
Median	0.274	0.198	0.254	0.198	0.273	0.202	0.281	0.236	0.268	0.241	0.278	0.227
Mean	0.273	0.205	0.274	0.270	0.270	0.280	0.280	0.270	0.270	0.274	0.274	0.231
Std Dev	0.061	0.050	0.050	0.054	0.054	0.051	0.051	0.056	0.056	0.047	0.047	0.050
Min	0.126	0.136	0.145	0.154	0.141	0.113	0.168	0.142	0.180	0.102	0.167	0.097
Max	0.586	0.360	0.455	0.360	0.547	0.355	0.463	0.374	0.520	0.565	0.391	0.354

Note: States denoted with a 1 represent the period with quota system, 1982–2001, while 2 represents the period with contract pricing system, 2002–2018. AL = Alabama, FL = Florida, GA = Georgia, NC = North Carolina, TX = Texas, and VA = Virginia.

We conducted a statistical *t*-test and *F*-test to determine the difference between the mean and variability of these prices between the periods. A 0.05 cut-off *p*-value was used to test statistical significance in this study. The results from this test (Table 2) suggest a clear difference in price patterns before and after the policy change for the majority of states studied. However, the test fails to reject that the means are different between the two periods in Texas and that the variances are different in North Carolina and Virginia. Despite our findings for Texas, we reject the hypothesis that the variances of the two periods are equal. The two-sample *t*-test also rejects the hypothesis that the means for North Carolina and Virginia from the two periods are equal. Ultimately, these tests confirm a significant difference between prices in the two periods for the majority of peanut-producing states.

The data also contained some missing values. If five or fewer values in a row were missing, then we used a random walk model to forecast these values. If more than five values were missing, then we forecasted those values using appropriate auto-regression estimates for each series using SAS statistical software. Figures 1–6 illustrate the price patterns for each individual state. Dashed lines indicate where data were split, and boxes highlight data points that were forecasted.

Methodology

We estimate market integration and price discovery patterns among grower-level peanut prices using causality structures identified through cutting-edge machine-learning algorithms applied to peanut prices from the relevant states. We develop the aforementioned causality structures using directed acyclic graphs (DAGs) (Pearl, 2009), which illustrate causal flow among a set of variables and do not contain cyclic paths (Dharmasena, Bessler, and Capps, 2016). Graphs consist of vertices and edges; in the DAGs, the edges are represented as arrows showing causal relationships among variables. For a given set of variables {A, B, C, D}, a DAG will only contain directed edges (e.g., $A \rightarrow B$) but not undirected edges (e.g., A—B) or cyclic paths in which a path the leads away from the variable and then returns to the same variable (e.g., $A \rightarrow B \rightarrow C \rightarrow A$).

We used a greedy equivalence search (GES) machine-learning algorithm to develop causality patterns among peanut prices across various states (Dharmasena, Bessler, and Capps, 2016; Kim

Table 2. Results from *t*-Test and *F*-Test of Mean Peanut Price and Variance of Price Series between Periods, 1982–2001 and 2002–2018

	Test	Calculated Value	Critical Value	*p*-Value	Results from the Hypothesis Test
AL	2-sample *t*-test	10.21	2.26**	0.000	Reject the null hypothesis that the means are equal
	F-test	2.06	1.32**	0.000	Reject the null hypothesis that the variances are equal
FL	2-sample *t*-test	8.45	2.26**	0.000	Reject the null hypothesis that the means are equal
	F-test	1.59	1.32**	0.003	Reject the null hypothesis that the variances are equal
GA	2-sample *t*-test	9.57	2.26**	0.000	Reject the null hypothesis that the means are equal
	F-test	1.44	1.32**	0.016	Reject the null hypothesis that the variances are equal
NC	2-sample *t*-test	6.12	2.26**	0.000	Reject the null hypothesis that the means are equal
	F-test	1.13	1.32	0.233	Fail to reject the null hypothesis that the variances are equal
TX	2-sample *t*-test	1.66	2.25	0.099	Fail to reject the null hypothesis that the means are equal
	F-test	2.02	1.34**	0.000	Reject the null hypothesis that the variances are equal
VA	2-sample *t*-test	7.45	2.26**	0.000	Reject the null hypothesis that the means are equal
	F-test	1.12	1.34	0.262	Fail to reject the null hypothesis that the variances are equal

Note: Significance level considered is *p*-value 0.05. AL = Alabama, FL = Florida, GA = Georgia, NC = North Carolina, TX = Texas, and VA = Virginia.

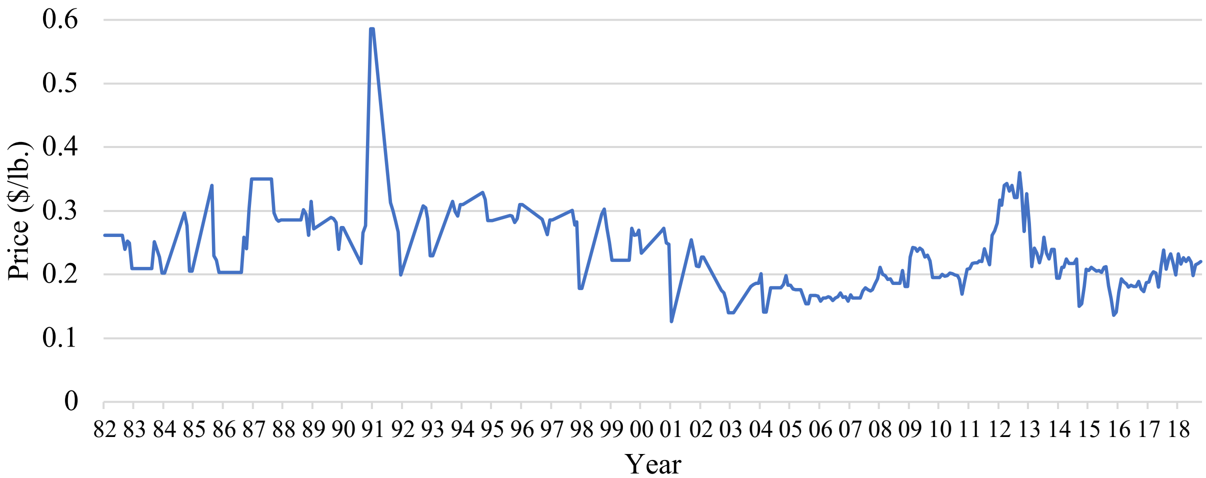

Figure 1. Alabama Monthly Peanut Price Received, 1982–2018

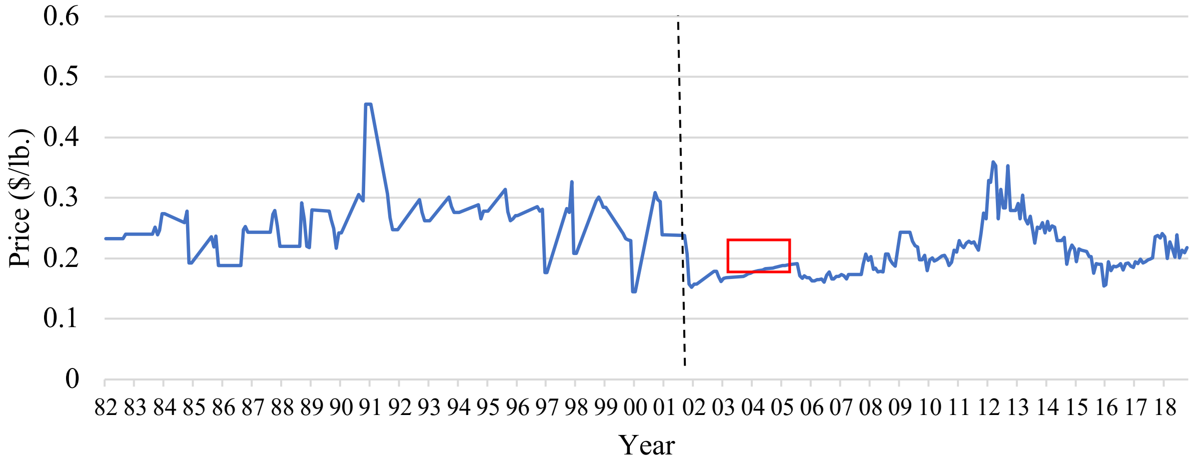

Figure 2. Florida Monthly Peanut Price Received, 1982–2018

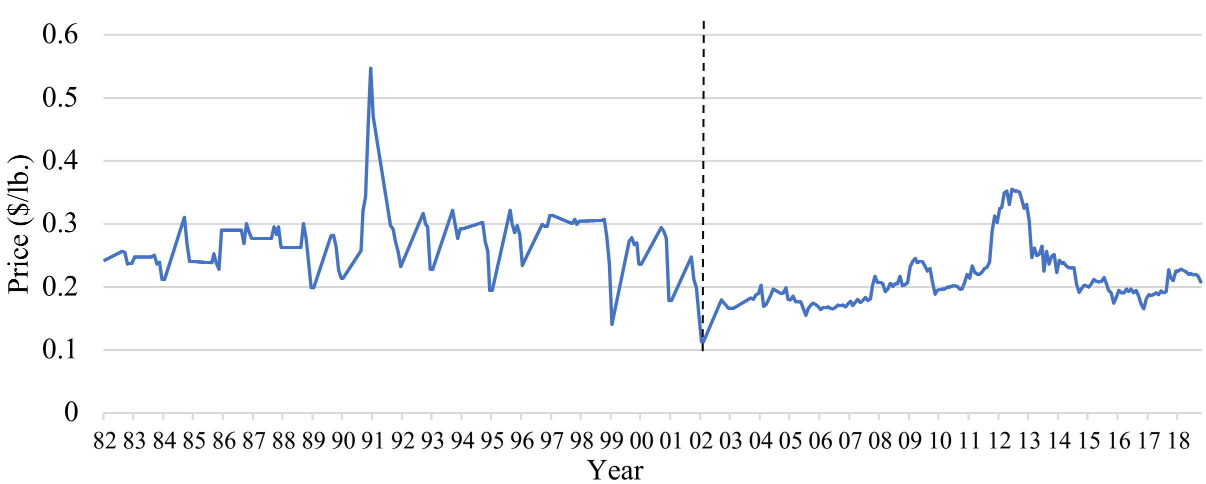

Figure 3. Georgia Monthly Peanut Price Received, 1982–2018

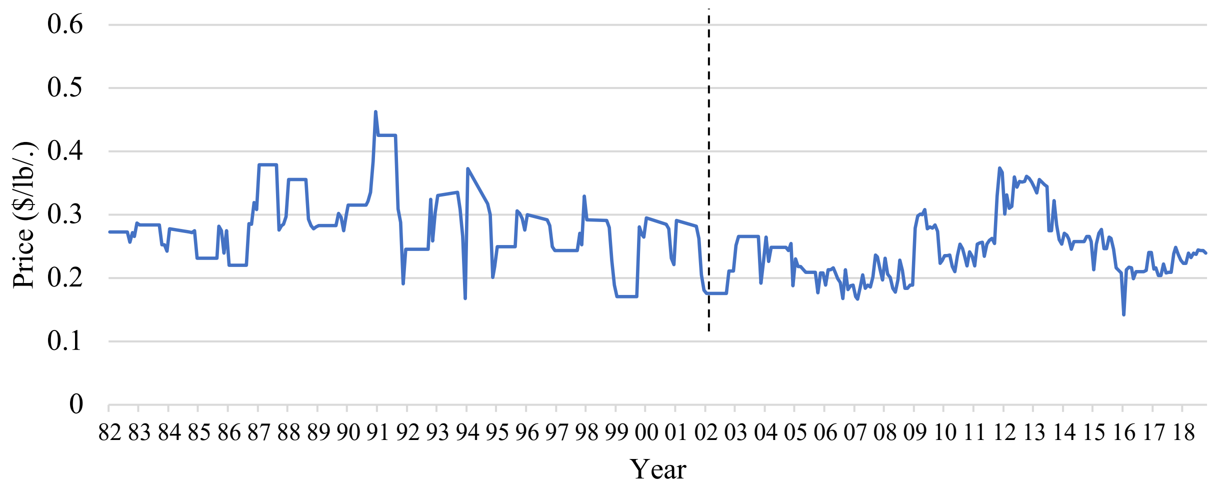

Figure 4. North Carolina Monthly Peanut Price Received, 1982–2018

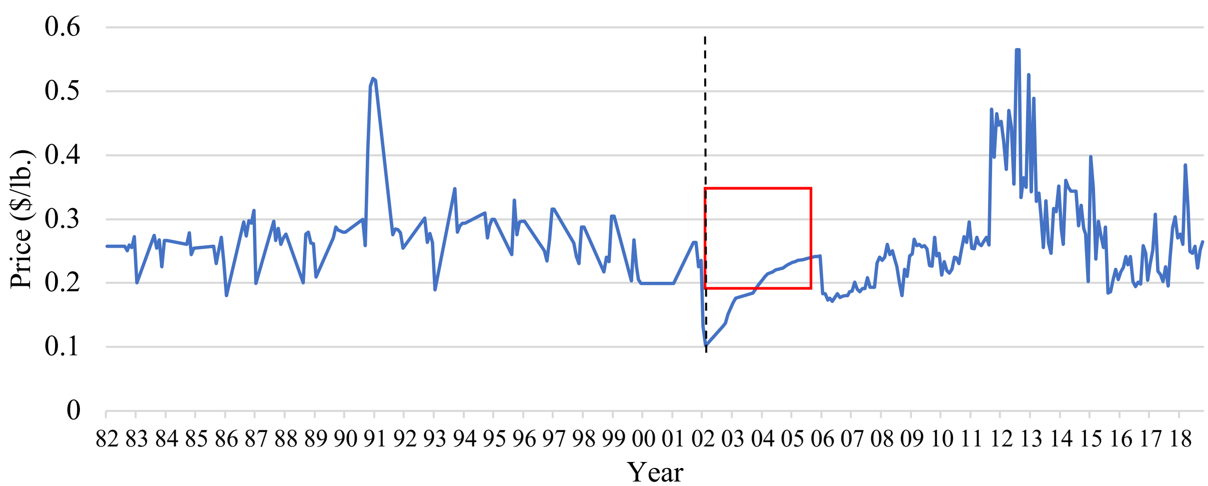

Figure 5. Texas Monthly Peanut Price Received, 1982–2018

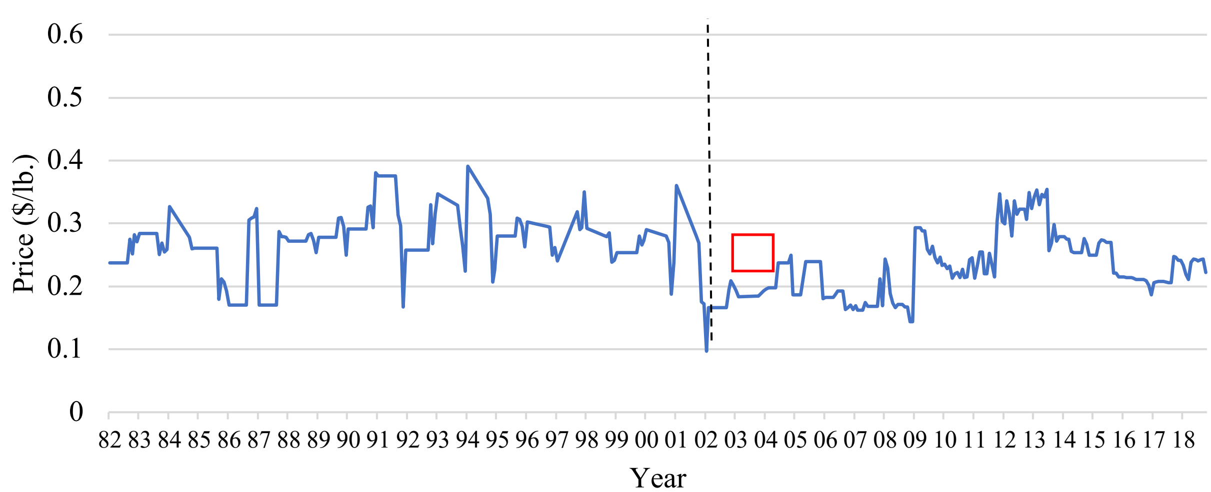

Figure 6. Virginia Monthly Peanut Price Received, 1982–2018

and Dharmasena, 2018. GES is operationalized through the TETRAD statistical package, which searches causal models with artificial intelligence and DAGs. According to Dharmasena, Bessler, and Capps and Kim and Dharmasena, GES finds the optimal causal structures to minimize a Bayesian information criterion (BIC) in two phases. First, the algorithm attempts to add edges to a DAG and scores each graph based on the BIC, repeating this process until a local maximum is reached. In the second phase, single edges are deleted until a local maximum is reached based on the score of DAG. Chickering (2002) explains the BIC approximation from the Schwarz loss function and the assumptions underlying GES. The following equation expresses the BIC approximation from Schwarz:

(1) $$S(\mathcal{G}, \boldsymbol{D}) = \ln p(\mathrm{D}|\hat{\theta}, \mathcal{G}^h) - \frac{d}{2}\ln m,$$

"where $\widehat{\theta}$ is the maximum-likelihood estimate of the unknown parameters, *d* is the number of free parameters (not equal to 0) of graph $\mathcal{G}$, and m is the number of observations in data, **D**. The $S(\mathcal{G}, \boldsymbol{D})$ function offers a trade-off between fit given by $\ln p(\mathrm{D}|\hat{\theta}, \mathcal{G}^h)$and parsimony is given by $\frac{d}{2}\ln m$" (Dharmasena, Bessler, and Capps, 2016, p. 168). The working of GES algorithm is based on three assumptions: causal sufficiency, causal faithfulness, and causal Markov conditions (see Dharmasena, Bessler, and Capps, 2016, for further explanation of these conditions).

Results

Figure 7 is the DAG of 1992–2001 peanut prices in six states, with two lags of price series. The marginal effects are denoted on the edges between variables, while the mean values are denoted in green on the lower right side of the state. Kim and Dharmasena (2018, p. 43) explain that

> Each edge with direction determines the predictor and predicted variables in the regression model. Each number on an edge is the estimated slope coefficient of the predictor variable when arrow-received variable (dependent variable) is regressed on every causing variable (independent variable).

Table 3 reports the resulting coefficients and *p*-values associated with Figure 7. All of the coefficients are significant at the 1% level or less. This analysis provides valuable information about how prices are related among these peanut-producing states.

Current-period prices in Georgia are positively influenced by prices from the previous two periods of Georgia. Current prices in Georgia and the previous-period price in Alabama have an impact on the current price in Alabama, which is the primary factor influencing current prices in Texas, which is a price sink. However, additional prices—such as the current, previous, and two period previous prices in Georgia—indirectly influence Texas prices through a causal chain. Texas prices from two previous periods also indirectly affect current-period prices in Alabama and therefore also indirectly influence current prices in Texas and Florida, creating causal chains. Virginia and Florida are also price sinks, with Virginia being influenced by North Carolina current prices and Florida receiving prices from previous-period prices in Florida, $FL_{(t-1)}$, and current-period prices in Alabama. North Carolina's current prices are influenced by the previous-period prices in North

Carolina, $NC_{(t-1)}$, and Texas, $TX_{(t-1)}$. In addition, North Carolina's current price is also indirectly influenced by the prices two periods ago in Texas, $TX_{(t-2)}$, and North Carolina, $NC_{(t-2)}$. Figure 7 illustrates these causal chain relationships.

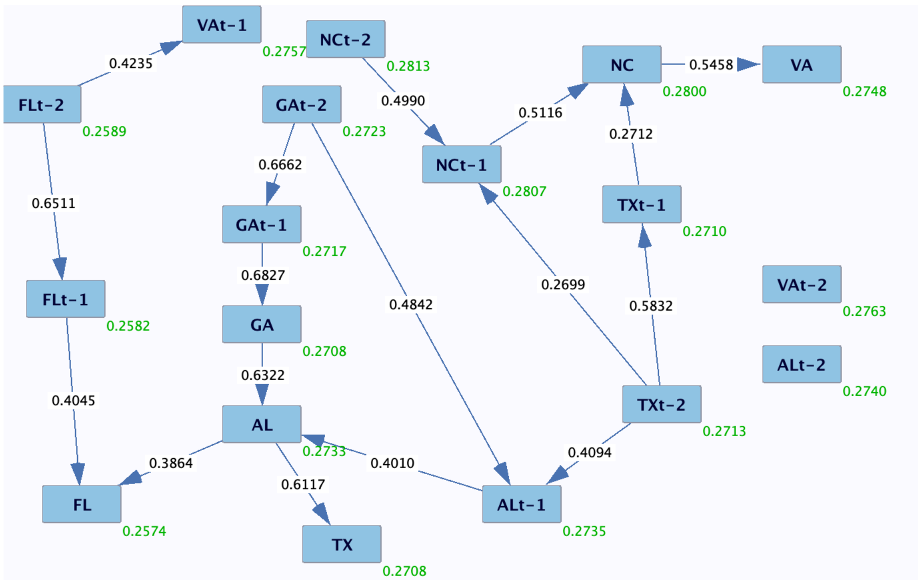

Figure 7. Directed Acyclic Graph (DAG) of Peanut Prices, 1982–2001

Table 3. Parameter Estimates for Each Edge, 1982–2001

From	To	Edge Coefficient	*p*-Value
GA	AL	0.6322	0.000
AL_{t-1}	AL	0.4010	0.000
NC	VA	0.5458	0.000
FL_{t-1}	FL	0.4045	0.000
NC_{t-1}	NC	0.5116	0.000
FL_{t-2}	VA_{t-1}	0.4235	0.000
TX_{t-2}	AL_{t-1}	0.4094	0.0001
TX_{t-2}	TX_{t-1}	0.5832	0.000
TX_{t-2}	NC_{t-1}	0.2699	0.0003
TX_{t-1}	NC	0.2712	0.0003
GA_{t-2}	GA_{t-1}	0.6662	0.000
NC_{t-2}	NC_{t-1}	0.4990	0.000
GA_{t-1}	GA	0.6827	0.000
AL	TX	0.6117	0.000
AL	FL	0.3864	0.000
GA_{t-2}	AL_{t-1}	0.4842	0.000
FL_{t-2}	FL_{t-1}	0.6511	0.000

Note: Significance level considered is *p*-value 0.05 AL = Alabama, FL = Florida, GA = Georgia, NC = North Carolina, TX = Texas, and VA = Virginia. AL_{t-1}, FL_{t-1}, GA_{t-1}, NC_{t-1}, TX_{t-1}, VA_{t-1}, AL_{t-2}, FL_{t-2}, GA_{t-2}, NC_{t-2}, TX_{t-2}, and VA_{t-2} represent peanut prices received by growers in periods $t-1$ and $t-2$ in Alabama (AL), Florida (FL), Georgia (GA), North Carolina (NC), Texas (TX), and Virginia (VA), respectively.

Figure 8 shows the DAG of 2002–2018 peanut prices, after the marketing quota system was discontinued. Table 4 reports the coefficients and p-values; all values are statistically significant at the 1% level. As in the 1982–2001 DAG, Texas is a price sink; however, current Texas prices are now influenced by the previous period's prices in Texas and Georgia. The current periods in Alabama, Florida, and Virginia are also price sinks. Current prices in Alabama are influenced by its previous periods price, $AL_{(t-1)}$, and the current price in Georgia. Prices in Georgia from two periods previous, $GA_{(t-2)}$, also impact current Alabama prices by influencing prices in Texas, $TX_{(t-1)}$, and Alabama, $AL_{(t-1)}$, which then directly and indirectly influence the current price in Alabama. Although Florida's previous price and Georgia's current prices are the only factors directly influencing the current price in Florida, prices from two periods ago in Texas, Georgia, and Florida all indirectly influence the price through various causal chains.

Table 4. Parameter Estimates for Each Edge, 2002–2018

From	To	Edge Coefficient	p-Value
GA_{t-2}	AL_{t-1}	0.5234	0.000
TX_{t-2}	TX_{t-1}	0.3307	0.000
NC_{t-2}	NC_{t-1}	0.7082	0.000
TX_{t-2}	VA_{t-1}	0.1605	0.000
GA_{t-1}	TX	0.9703	0.000
FL_{t-1}	FL	0.3936	0.000
NC	VA	0.4627	0.000
GA	FL	0.5141	0.000
GA_{t-2}	TX_{t-1}	0.9652	0.000
AL_{t-1}	AL	0.284	0.000
TX_{t-2}	FL_{t-1}	0.1131	0.000
NC_{t-1}	NC	0.6097	0.000
VA_{t-2}	VA_{t-1}	0.6941	0.000
TX_{t-1}	TX	0.3313	0.000
GA_{t-1}	GA	0.856	0.000
GA_{t-2}	GA_{t-1}	0.9436	0.000
FL_{t-2}	FL_{t-1}	0.4389	0.000
VA_{t-1}	VA	0.5151	0.000
GA_{t-2}	FL_{t-1}	0.2786	0.0001
GA	AL	0.6705	0.000
TX_{t-1}	GA	0.0729	0.0001
GA	NC	0.363	0.000
TX_{t-2}	NC_{t-1}	0.1461	0.000
AL_{t-2}	AL_{t-1}	0.4004	0.000

Note: Significance level considered is p-value 0.05 AL=Alabama, FL=Florida, GA=Georgia, NC=North Carolina, TX=Texas and VA=Virginia. AL_{t-1}, FL_{t-1}, GA_{t-1}, NC_{t-1}, TX_{t-1}, VA_{t-1}, AL_{t-2}, FL_{t-2}, GA_{t-2}, NC_{t-2}, TX_{t-2}, and VA_{t-2} represent peanut prices received by growers in periods t and $t-1$ in Alabama (AL), Florida (FL), Georgia (GA), North Carolina (NC), Texas (TX), and Virginia (VA), respectively.

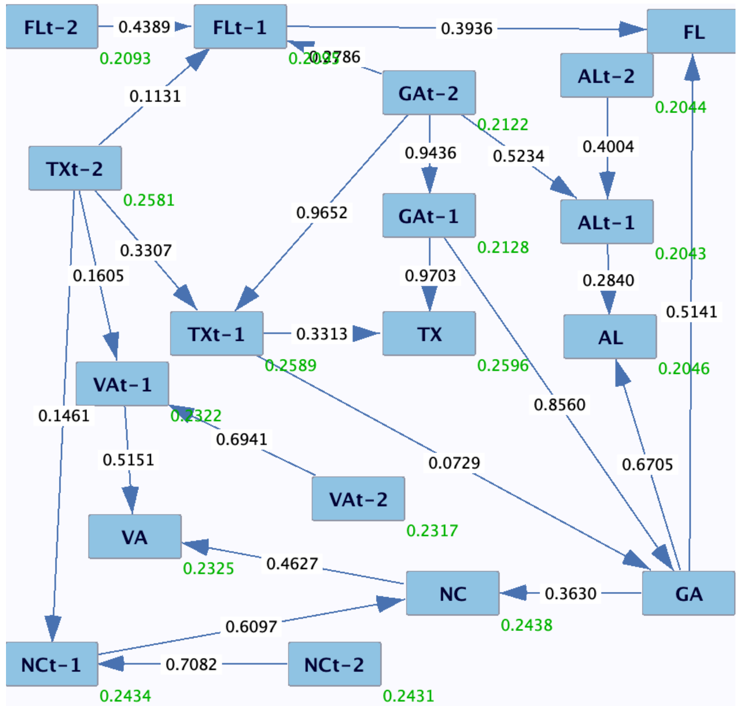

Figure 8. Directed Acyclic Graph (DAG) of Peanut Prices, 2002–2018

The current price in Virginia receives signals from the current price in North Carolina and the previous price in Virginia. Previous-period prices in Texas and Georgia also indirectly influence the price in Virginia. North Carolina's current price receives signals from its price in the previous period and the current price in Georgia. The current price in Georgia is influenced by the prices from the two consecutive previous periods in Georgia and Texas. This results in previous Texas and Georgia prices influencing the current North Carolina price. Ultimately, the previous prices from two periods ago in Texas, $TX_{(t-2)}$, and Georgia, $GA_{(t-2)}$, indirectly influence the current prices in all states. On the contrary, prices from two periods ago in Virginia, $VA_{(t-2)}$; Florida, $FL_{(t-2)}$; and Alabama, $AL_{(t-2)}$ only influence their respective current prices. North Carolina's price from two periods ago, $NC_{(t-2)}$, indirectly influences its current price and, more indirectly, Virginia's current price.

Conclusions and Implications

Georgia and Texas are price leaders: their past and current prices influence current prices in the majority of other states in both periods. Current- and previous-period prices in Georgia are strictly exogenous in the first period, 1982–2001. In the 2002–2018 period, previous-period prices in Georgia are also strictly exogenous, while the current price is weakly exogenous (GA causes prices of AL, FL, and NC and is caused by prices from GA and TX one period past). The price from the preceding periods is also a major determinant in current-period prices for almost all states. After 2002, the current price in all six states studied is directly influenced by its price in the previous period. Prior to 2002, current prices in Florida, Alabama, Georgia, and North Carolina are directly influenced by their respective prices from the preceding period; however, prices in Texas and Virginia are not influenced by their prices from the previous period.

Knowledge of direct and indirect causal relationships among peanut prices in these states is expected to be useful to peanut producers, marketers, and government policy makers to design national and state-level peanut-marketing programs.

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