Spatial sugar price transmission: an exploration in Florida, Texas, and Louisiana

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This study examines the interstate sugar price relationships between Florida, Texas, and Louisiana, which are the major sugarcane production states in the continental United States. We employ vector autoregression (VAR), Granger causality, forecast error variance decomposition, impulse response function, and structural break methods to conduct a time-series analysis on weekly sugar price data from October 2019 to December 2022. The results of the VAR model indicate that historical sugar prices in Florida consistently have a significant impact on current sugar prices in Texas and Louisiana. Our analysis also demonstrates that sugar prices in Florida Granger-cause those in Texas and Louisiana, sugar prices in Texas Granger-cause those in Florida, and sugar prices in Louisiana Granger-cause those in Florida. Finally, we reveal that the primary source of forecast error variance for all three states originates from sugar price shocks in Texas. These findings underscore the importance of real-time price monitoring and intergovernmental coordination to mitigate supply chain disruptions, offering actionable insights for policymakers to stabilize regional markets. For researchers, this study establishes a foundation for exploring nonlinear price dynamics and long-term structural shifts in agricultural commodities, while industry stakeholders gain empirical evidence to navigate volatility and optimize decision-making in a complex trade environment.

Keywords:
sugar,
price transmission,
vector autoregression

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Introduction

Sugar and sweeteners are significant components in the United States (US) food market, and the US sugar industry has a pivotal influence on domestic and global markets, ranking among the world's leading producers and consumers of sugar (OECD–FAO 2023). In recent years, the industry has faced numerous challenges, including climate change impacts on crop yields, shifting consumer preferences toward healthier alternatives, and international trade tensions affecting sugar prices (Zhao–Li 2015, Alsubhi et al. 2022, McConnell et al. 2010). Within this complex landscape, understanding the dynamics of sugar prices across major sugar-producing regions is crucial for industry stakeholders, policymakers, and consumers alike.

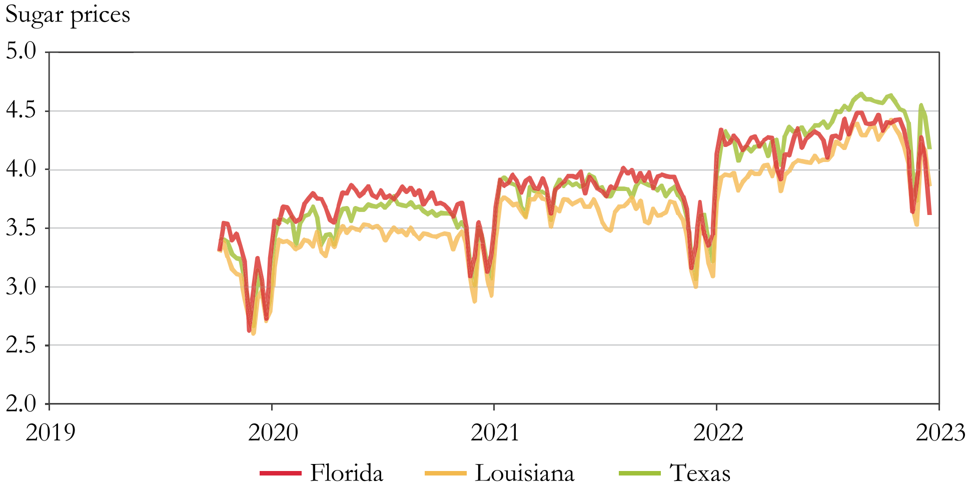
Florida, Texas, and Louisiana are the primary sugarcane-producing states in the continental US, collectively accounting for over 90% of domestic sugarcane production (Shahbandeh 2023). With a long history of sugar production, these states shape the domestic sugar market and significantly influence the nation's position in global sugar trade (Abadam 2021). However, despite their importance, a notable lack of research has been conducted regarding spatial price transmission within the US sugar industry, particularly among these key producing states.

This study fills this research gap by investigating interstate sugar price relationships between Florida, Texas, and Louisiana. Figure 1 illustrates weekly sugar prices across these three states from October 6, 2019 to December 18, 2022, revealing that sugar in Florida commanded the highest premium of the three states; however, Texas surpassed Florida as the state with the highest sugar prices since April 2022. Therefore, we are motivated to examine whether this change also signifies a broader change in sugar price dynamics. Specifically, does this shift represent a structural break in the sugar market, signifying an important disruption in price dynamics? Employing vector autoregression (VAR) models, Granger causality tests, forecast error variance decomposition, and impulse response functions, we reveal the patterns and drivers of sugar horizontal price transmission across these states. We also evaluate the changes in sugar price dynamics by conducting a structural break test on our VAR models, considering potential policy interventions or market shocks that may have disrupted established price relationships.

Understanding these price dynamics is essential, and this study contributes to the current literature in three significant ways. First, a dearth of research on spatial price transmission within the US sugar industry remains and our study addresses this research gap. Second, our investigation of US sugar price patterns provides valuable insights for policymakers tasked with designing and implementing sugar policies that balance producer interests with consumer welfare. Moreover, it equips producers and industry stakeholders with the knowledge to make more informed decisions in an increasingly volatile food market. Finally, we identify the Texas border inspection policy on commercial trucks as a likely factor influencing the shift in Texas' sugar prices relative to the other two states. Our study also contributes to broader discussions on food security in the face of climate change and evolving consumer preferences.

Figure 1

Weekly sugar prices in Florida, Texas, and Louisiana



Note: weekly price data cover the period from October 6, 2019 to December 18, 2022.

Literature review

The US sugar industry has undergone significant changes in recent decades, characterized by consolidation and technological advancements. According to Abadam (2021), a decline in the number of sugarcane and sugar beet farms in the US has occurred over the past two decades, while the average harvested area has increased. This trend toward larger, more efficient operations has implications for market structure and potentially for price dynamics across producing regions.

Price transmission in agricultural markets has been a subject of extensive research, with studies focusing on various commodities and geographical contexts. For example, Aragrande et al. (2016) examined horizontal price transmission in the European Union (EU) sugar sector, demonstrating price transmission between the world and EU domestic sugar markets and between significant sugar-producing EU member states. Similarly, Jacomini–Burnquist (2018) identified bidirectional price transmission between producers and retailers in the Brazilian sugar market, concluding that products tend to be more sensitive to price decreases than price increases. Chisanga et al. (2015) revealed weak price transmission from the world sugar market to the Zambian domestic sugar market. The authors' analysis indicated that the market structure may reduce the potential economic benefits of investment and trade. However, comprehensive studies on sugar price transmission within the US, particularly between major producing states do not exist.

Several factors have been found to influence sugar prices in the US market, potentially resulting in consistent price drops each year. First, the sugar harvest season typically occurs during the fall and early winter (Abadam 2022). The increased supply of domestic sugar during these months can result in a temporary oversupply in the market, putting downward pressure on prices. Government policies, such as the sugar program and import quotas, have a significant influence on shaping domestic sugar prices (USDA ERS 2023). October and December usually have the top two raw sugar tariff rate quotas for US monthly sugar imports (Diaby 2023). The resulting increase in imported sugar supply can potentially reduce prices. Additionally, the disclosure requirements for genetically engineered ingredients on food labels that were implemented in 2016, particularly for sugar beet products, have negatively affected the sugar beet industry, contributing to reducing the price gap between refined cane and beet sugar.

The impact of weather events and climate change on crop yields can cause sugar supply fluctuations and price volatility. As noted by Zhao–Li (2015), sugarcane cultivation is characterized by considerable fluctuations due to natural disasters and annual variations in rainfall and temperature. Furthermore, sugar production affects the surrounding environment, with negative impacts on biodiversity, water resources, air quality, and soil erosion, which reduces soil quality, as demonstrated by Cheesman (2004). Global market dynamics such as international sugar prices and exchange rates also affect domestic prices, albeit such effects are moderated by trade policies. Chisanga et al. (2015) found that a dynamic increase in sugar production and exports following industrial privatization in 1995 and the prohibition of increased sugar imports during the USDA marketing year, coupled with the rising input costs of sugar production, markedly increased raw sugar price.

Regional differences in sugar production efficiency and costs between Florida, Texas, and Louisiana have been documented in previous studies. Lynn Kennedy et al. (1998) found that Florida records higher sugarcane production yields and lower processing costs than Texas and Louisiana, while Louisiana benefits from comparatively lower production costs that are attributable to lower cash expenses. These differences in production characteristics may contribute to variations in these states' price dynamics.

While the previous research has provided insights into various aspects of sugar markets and price transmission, a significant gap in understanding the spatial price dynamics within the US sugar industry remains, particularly among the major sugarcane-producing states. This study addresses this gap, with valuable contributions to academic literature and practical industry knowledge. By analysing the price transmission patterns between Florida, Texas, and Louisiana, we enhance the understanding of the US sugar market's functioning and provide insights that can inform policy decisions and industry strategies in an evolving agricultural landscape.

Empirical design

Data description

This study uses weekly retail food sales on sugar and sweetener prices in Florida, Texas, and Louisiana, ranging from week 40 in 2019 to week 50 in 2022 with a total of 168 observations. To calculate the sugar unit price (the variable of interest in our study), we divide the total sales value by the total units sold, choosing this period based on data availability and comparability. The raw data used in this study are sourced from the weekly retail food sales series published by the USDA's ERS, which provides state-level totals across 10 product categories, including sugar and sweeteners (USDA ERS 2023). We chose the primary sugarcane-producing states of Florida, Texas, and Louisiana as the focus of this study due to our interest in investigating the price linkage between these regions.

Stationarity testing

We test for stationarity in our time-series sugar price data by performing augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests, confirming that all three series are stationary, as shown in Table 1.

Table 1

Unit root testing results for Florida, Texas, and Louisiana time-series data

Denomination	Florida	Texas	Louisiana	Result
ADF				
test statistics	−4.00	−3.46	−3.70	
lag order parameter	5	5	5	
p-value	0.01**	0.05**	0.03**	stationary**
PP				
test statistics	−36.75	−37.15	−35.96	
truncation lag parameter	4	4	4	
p-value	0.01***	0.01***	0.01***	stationary***
KPSS				
test statistics	2.15	2.53	2.49	
truncation lag parameter	4	4	4	
p-value	0.01***	0.01***	0.01***	stationary***

Note: * $p < 0.10$ (confidence level of 90%), ** $p < 0.05$ (confidence level of 95%), and *** $p < 0.01$ (confidence level of 99%).

The ADF, PP, and KPSS tests to examine the presence of a unit root are expressed as follows:

$$\Delta p_{it} = a_0 + \gamma p_{it-1} + \sum_{j=2}^{n} \varphi_i \Delta p_{it-1} + \varepsilon_t \tag{1}$$

$$p_{it} = b_0 + \delta p_{it-1} + \varepsilon_t \tag{2}$$

$$KPSS = t^{-2} \sum_{t=1}^{t} \frac{S_t^2}{\sigma^2} \tag{3}$$

where p_{it} is the sugar price in state i at time t, $\Delta p_{it} = (p_{it} - p_{it-1})$, a_0 and b_0 are drift terms, ε_t is the error term, S_t^2 is the partial sum of the errors, and σ^2 is the estimate of the long-term variance of the errors. The joint hypothesis is $H_0 = \gamma = a_0 = 0$ and the alternative hypothesis indicates the series is stationary.

Optimal lag selection

We determine the optimal lag length by comparing five common statistical criteria, encompassing Akaike information criterion (AIC), Bayesian information criterion (BIC), Hannan–Quinn information criterion (HQ), Schwarz criterion (SC), and the final prediction error (FPE). Our results reveal that the AIC, HQ, and FPE criteria suggest a relatively larger lag selection of 4, while BIC and SC suggest a lag of 2. We use a lag of 2 in the following analysis as our data are limited and we aim for a more parsimonious model to avoid overfitting. We use this lag length to construct our regression model in subsequent sections.

Economic model estimation

The VAR model serves as the analytical framework for our time-series data analysis. This model is a powerful tool for investigating the dynamic behaviour of economic time-series and subsequent forecasting (Ventura 2020). This approach can also capture potentially unobserved variations in the data that may influence the relationship between variables.

In addition, we adopt the seasonal–trend decomposition (STL) using the locally estimated scatterplot smoothing (LOESS) method to decompose the seasonality and trend components inherent to each state's dataset. Notably, due to the similarity in performance observed among the STL results in Texas, Florida, and Louisiana, we randomly selected Texas as the reference for decomposing seasonality. We employ seasonal terms rather than weekly fixed effects because of the limited number of data points. We initially included a trend term in the VAR model; however, a comparison of the AIC and BIC values for models with and without the trend term indicated that the model without the trend term exhibited lower AIC and BIC values, indicating better model performance. Specifically, the model for Florida, Texas, and Louisiana can be expressed as follows:

$$\begin{aligned} p_{i,t} = b_0 &+ \beta_{i1,1}\, p_{1,t-1} + \beta_{i2,1}\, p_{2,t-1} + \beta_{i3,1}\, p_{3,t-1} + \beta_{i1,2}\, p_{1,t-2} \\ &+ \beta_{i2,2}\, p_{2,t-2} + \beta_{i3,2}\, p_{3,t-2} + \beta_3\, s_T + \varepsilon_{i,t} \qquad \mathrm{i} = 1,2,3 \end{aligned} \tag{4}$$

where b_0 is an intercept term, p_{it} is the sugar price level of state i at time t, and e_t is the error term. S_t denotes the seasonality of Texas that we include as the exogenous factor to enhance the VAR model's precision, which we calculate using a LOESS approach, which employs a moving window to fit a weighted regression line to the data for the purpose of trend removal (Cleveland et al. 1990).

Results and discussion

VAR results

The VAR regression results in Table 2 reveal that the sugar prices in the three states are correlated with one another's past sugar prices. The first and second lags of Florida's price in column (A) are statistically significant at a 99% confidence level, and the second lag of Texas's price is statistically significant at a 90% confidence level. The seasonality index is statistically significant at a 99% confidence level for Florida prices. Similarly, for the Texas sugar price in column (B), the first and second lags of Florida prices are statistically significant at a 99% confidence level. The first lag of Texas' price is statistically significant at a 99% confidence level and the second lag of Texas' price is statistically significant at a 95% confidence level. The seasonality index is statistically significant at a 99% confidence level for Texas' prices. For the Louisiana sugar price in column (C), the first and the second lags of Florida price are statistically significant at a 99% confidence level and the first lag of Louisiana is statistically significant at a 90% confidence level. The seasonality index is statistically significant at a 95% confidence level for Louisiana's prices. These results indicate that sugar prices in these states are interdependent and significantly more influenced by Florida's past prices. Significant seasonal coefficients across all columns reveal a strong seasonal component to sugar prices, which is likely due to agricultural cycles.

Our VAR model results demonstrate that sugar prices in Texas, Florida, and Louisiana are correlated, with Florida and Texas sugar price lags exerting a stronger negative influence on other states' sugar prices. These findings provide useful insights for understanding sugar price dynamics within and between states. While Table 2 provides immediate coefficients, the full dynamics of the VAR can be better understood using forecast error variance decomposition (FEVD) and the impulse response function (IRF). In addition to the influence of local, state-specific events on local sugar prices, the rules or events that impact sugar prices in other states could have an indirect impact on sugar prices on other states.

We use a shift in Texas's sugar price in April 2022 to assess whether this change was structurally significant by conducting a structural break test. To obtain a deeper understanding of the interactions and feedback between variables and the dynamic characteristics of the sugar prices in Texas, Florida, and Louisiana, we employ Granger causality, FEVD, and the IRF in our analysis.

Table 2

Vector autoregression model

Denomination	Equation FL (A)	Equation TX (B)	Equation LA (C)
TX_{t-1}	0.06 (0.18)	0.57*** (0.15)	0.16 (0.14)
LA_{t-1}	0.02 (0.19)	−0.02 (0.17)	0.41* (0.16)
FL_{t-1}	0.60*** (0.14)	0.61*** (0.12)	0.52*** (0.11)
TX_{t-2}	0.46** (0.17)	0.42** (0.15)	0.25 (0.14)
LA_{t-2}	0.12 (0.19)	0.24 (0.16)	0.23 (0.16)
FL_{t-2}	−0.59*** (0.12)	−0.96*** (0.10)	−0.74*** (0.10)
Seasonal index	0.39*** (0.07)	0.22*** (0.06)	0.18** (0.06)
Constant	1.34*** (0.20)	0.60*** (0.17)	0.60*** (0.16)
Adjusted R^2	0.84	0.92	0.91
F-statistics	125.5	274.7	239.9

Note: standard errors are in parentheses. * denotes 10% significance, ** denotes 5% significance, and *** denotes 1% significance.

Structural break test implications

The structural break in Texas that occurred in April 2022 coincided with the implementation of new inspection rules in the state that disrupted cross-border supply chains by delaying commercial truck entries from Mexico. While other factors such as seasonal harvest cycles or global price trends could theoretically contribute to price shifts, the temporal alignment of the break with the policy's implementation and its immediate supply chain impacts imply that this intervention could be a significant driver. Public perceptions revealed that the policy raised consumers' costs under a high inflation environment while reducing fresh vegetable supplies from Mexico (Weber–Coronado 2022). This policy shock could be a potential factor contributing to the unexpected surge in Texas' sugar prices, deviating from its typical historical pattern.

To investigate whether this policy shock is correlated with a fundamental shift in the underlying sugar price dynamics, we conduct a structural break analysis using the Chow test on our VAR model. The analysis is intended to identify significant changes in the relationships between the VAR residuals around the time of the policy's implementation. The significant p-value of the Chow test provides robust evidence of a structural break in April 2022, confirming that the dynamics governing sugar prices experienced a notable shift during this period. This structural change likely reflects broader economic and market disruptions caused by the new border inspection policies, highlighting their impact on the sugar supply chain and pricing mechanisms in Texas.

Granger causality interpretation

We further validate the VAR estimation results using Granger causality tests to examine whether lags in sugar prices in one state are helpful for forecasting other states' sugar prices. Table 3 demonstrates that Florida's sugar price Granger-causes that of Texas and Louisiana at a 99% confidence level, Texas's sugar price Granger-causes that of Florida at a 99% confidence level as well as Louisiana at a 90% confidence level, and Louisiana's sugar price Granger-causes that of Florida at a 99% confidence level. This implies that past sugar prices in Florida and Texas are valuable for predicting prices in other states. Therefore, Granger causality tests confirm that the sugar prices in these three states are mutually dependent and changes in one state's sugar price can be transmitted to other states.

Table 3

Granger causality test

Df.1[a)]	Df.2[b)]	F-stats	P-value	Conclusion
161	163	59.93	0.00***	FL Granger-causes TX
161	163	43.30	0.00***	FL Granger-causes LA
161	163	10.46	0.00***	TX Granger-causes FL
161	163	2.28	0.10*	TX Granger-causes LA
161	163	0.69	0.50	LA does not Granger-cause FL
161	163	6.63	0.00***	LA Granger-causes TX

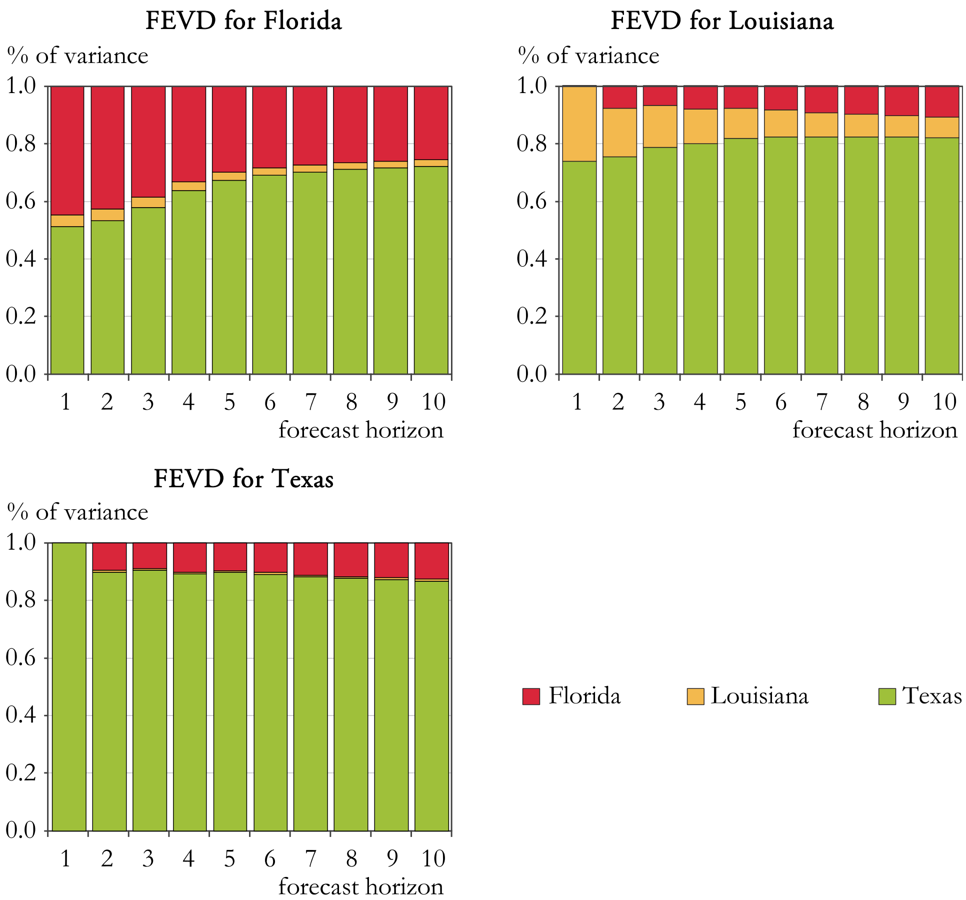
a) Df.1 refers to the numerator degrees of freedom.
b) Df.2 refers to the denominator degrees of freedom.
Note: * denotes 10% significance, ** denotes 5% significance, and *** denotes 1% significance.

Forecast error variance decomposition analysis

FEVD is a widely used statistical method for determining the portion of variance in a forecast error predicting future values due to structural shock. Figure 2 illustrates the FEVD for Texas, Louisiana, and Florida over 10 forecast horizons. The figure demonstrates that the three states share a common pattern of higher percentage values for their own changes in the first forecast horizon, indicating that the states' own shocks are the primary source of forecast error variance for near future sugar prices; however, this influence gradually diminishes as the forecast horizon extends. Figure 2 shows that the considerable forecast error variance for Texas, Florida, and Louisiana can be explained by the sugar price shock from Texas. Florida's price shock also has an influence on explaining these forecast error variances, with a limited contribution. Notably, Louisiana's sugar price only has a limited influence on its own price's forecast error variance and has almost no effect on that of the other two states. The FEVD results largely correspond with the outcomes of the Granger causality test, meaning that the information from Texas's and Florida's prices are more useful in predicting other states' sugar prices.

Figure 2

FEVD for Florida, Louisiana, and Texas future sugar price

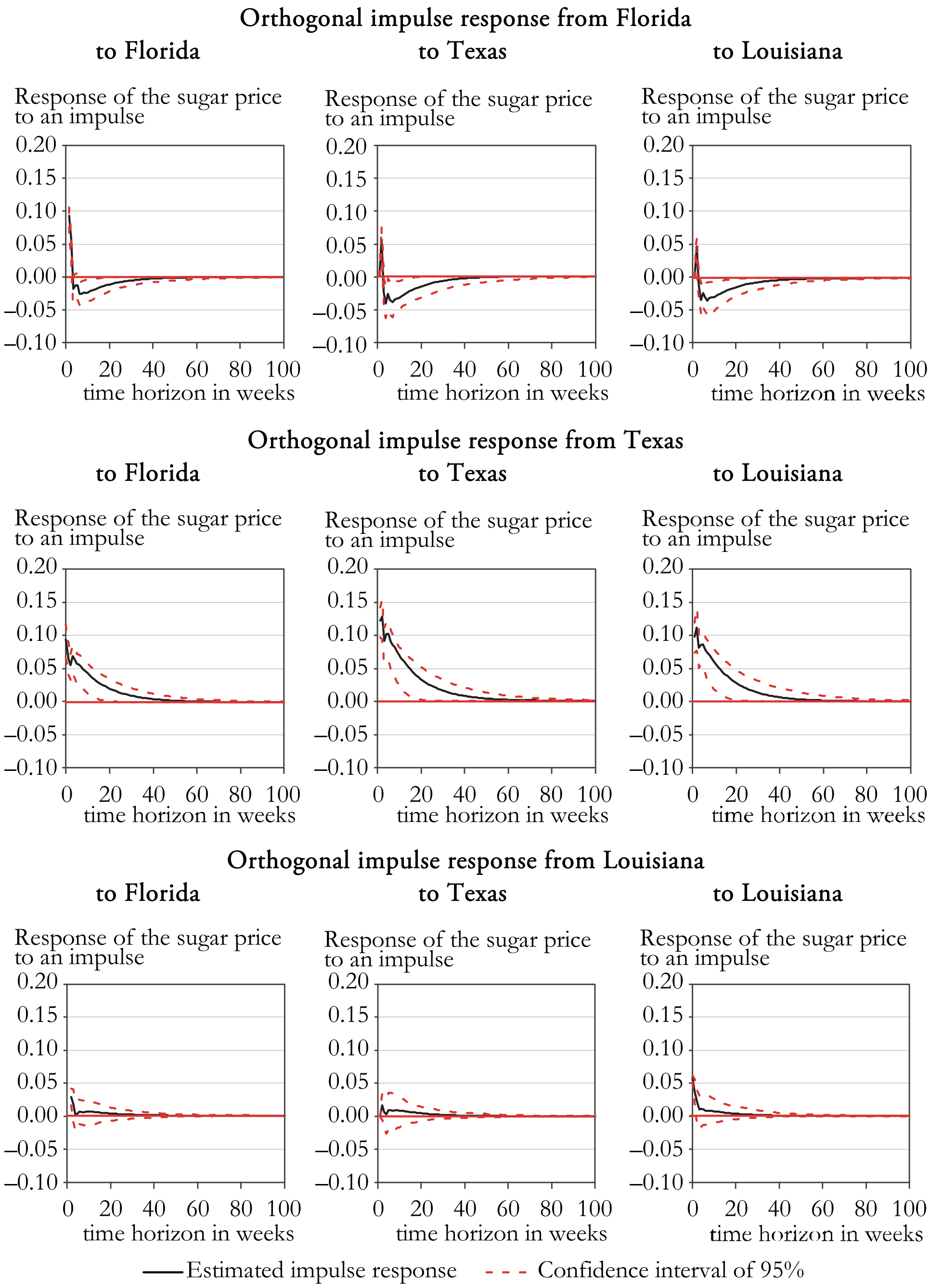


Impulse response function identifications

The IRF identifies the effect of a one-time shock to one of the variables in a model on the other variables over time. This approach enables us to analyse the transmission of sugar price shocks within the system and the magnitude of their impact on the sugar prices of each state. The IRF results are obtained using Cholesky decomposition to orthogonalize shocks. We determine variable ordering based on our Granger causality results, with Florida (the strongest Granger-cause of price changes in Texas and Louisiana) ordered first, followed by Texas and Louisiana. This ordering reflects the directional influence identified in the analysis. Robustness tests with alternative orderings yield qualitatively similar results, and future studies could explore additional permutations to further validate these dynamics.

Figure 3

IRF for Florida, Texas, and Louisiana



As shown in Figure 3, approximately 15–20 periods are required to eliminate the shock effect from Florida, and it takes around 20 periods for the response to Texas's shock effect to stabilize. There is insufficient statistical evidence to conclude that Louisiana's shock effect had an immediate or measurable impact on each state's sugar prices. The IRF results demonstrate that a positive shock from Texas will have a positive impact on other states' sugar prices, while a shock from Florida can have negative effects on other states.

Conclusion

While previous research has confirmed that the sugar prices among Florida, Texas, and Louisiana exhibit stationarity, this study demonstrated the interconnectedness of sugar prices across these states. The findings can help policymakers strategically tailor support programs to the unique needs of each region. The findings from VAR analysis indicate that the sugar prices in Texas, Florida, and Louisiana are highly reliant (99% confidence level) on Florida's previous sugar prices, which are related to the first lag in their own sugar prices at least at the 90% confidence level. In addition, the Granger causality results reveal that Florida's sugar prices Granger-cause those in the other two states and Texas Granger-causes those in the other two states as well. The results of FEVD analysis confirm that Texas, Florida, and Louisiana sugar prices have a significantly higher impact on their respective states compared with their influence on other states.

By understanding the complex dynamics of the sugar market, policymakers can implement agricultural/sugar support programs that are more effective in stabilizing prices, supporting producers, and ensuring a reliable sugar supply for consumers. Florida's historical price influence and Texas's dominance in forecast error variance suggest that policymakers should prioritize these states in real-time price monitoring systems to anticipate and mitigate interstate volatility. For example, targeted buffer stock policies in Florida could stabilize regional prices, while Texas-focused supply chain resilience programs such as diversifying import routes or subsidizing logistics during disruptions might diminish nationwide spillovers. In addition, our results contribute to greater market transparency by providing insights into the factors that influence sugar prices, and can empower producers, processors, and consumers to make informed decisions and advocate fair market practices.

A significant structural change occurred in April 2022 that coincided with the implementation of Texas' new inspection requirements, which raised the cost of consumers in a high inflation environment while reducing fresh vegetable supplies from Mexico. This external shock may plausibly account for the unexpected surge in Texas' sugar prices beyond its typical historical pattern. The structural break associated with Texas's border policy emphasizes the need for intergovernmental coordination to avoid abrupt trade disruptions. Federal agencies could establish contingency frameworks such as emergency import quotas or expedited customs protocols to protect domestic markets from subnational policy shocks. Finally, strong seasonal components across all three states' prices highlight opportunities to align agricultural subsidies or crop insurance programs with seasonal risk patterns to ensure producer stability without distorting market signals.

Somewhat unexpectedly, the FEVD also reveals that a substantial proportion of the forecast error variance for Texas, Florida, and Louisiana can be attributed to the price shock in Texas, while the influence of Florida's prices on the forecast error variance is relatively limited. Nonlinear relationships within the price dynamics could be a plausible explanation; however, we must note that this consideration is not investigated in the current study due to data limitations. When suitable data become available, future research can further explore this unexplained concern and examine long-term sugar price dynamics, allowing for a more comprehensive and accurate assessment and enhancing the overall robustness of our findings. Moreover, it is crucial to investigate why the observed upward trend in sugar prices is not reflected in the stationary test results.

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