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RESEARCH ARTICLE

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An investigation of the price discovery role of futures markets: A dynamic time warping analysis of the United States corn markets

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Abstract

Futures markets are critical to price discovery and often dominate spot markets. We analyze the linkages between daily corn futures and spot prices in the United States using dynamic time warping. This nonparametric pattern recognition technique has several advantages over traditional time series methods. First, it can detect multiple changes in the lead-lag associations between the two prices within short intervals; the duration with which one series leads or lags another is not assumed to be fixed. Second, the method can be applied to time series without regard to their stationarity properties. This greatly expands the scope of this method to accommodate a wide range of time series. Third, it lends itself well to studying small samples, which econometricians encounter routinely. Fourth, the results are presented intelligibly using intuitive visualizations. Our results show that futures markets are critical to price discovery; nevertheless, spot markets dominate futures markets intermittently. We discuss the results in detail, setting them in the proper context. [EconLit Citations: C14, C32, Q02, Q11].

Abbreviations: DAG, Directed acyclic graphs; DTW, Dynamic time warping; FOB, Free-on-board; PNW, Pacific Northwest; USDA, United States Department of Agriculture; USDA-AMS, United States Department of Agriculture-Agricultural Marketing Services.

KEYWORDS
corn prices, dynamic time warping, futures markets, nonparametric methods, price discovery, time series analysis

1 | INTRODUCTION

Futures contracts play a crucial role in commodity markets by facilitating price discovery and providing a means for buyers and sellers to hedge risks associated with price volatility. This helps stabilize commodity prices and mitigate potential losses (Ferris, 2005; Tomek & Kaiser, 2014). However, speculation in futures markets can introduce instability in commodity prices (de Jong et al., 2022). According to standard finance theories, the futures price of an asset is influenced by various factors, including the risk-free interest rate, the capitalized flow of marginal convenience yield, the cost of physical storage, and the spot price (Pindyck, 2001). For this reason, one might surmise that spot markets lead futures markets. However, studies have shown that futures prices may dominate spot prices (Garbade & Silber, 1983); in such cases, the former may be presumed to lead the latter. This study contributes to the ongoing debate regarding the associations between futures and spot prices.

More specifically, we examine the lead-lag associations between futures and spot prices of corn, one of the most widely traded commodities in the world. We focus on the United States corn markets, as the United States is the largest corn producer and exporter globally. This study is methodologically novel. We employ dynamic time warping (DTW), a nonparametric machine learning technique, instead of more traditional methods such as Granger causality, cointegration, vector error correction, and time-difference analysis, or more recently used methods such as directed acyclic graphs (DAGs) and wavelet decomposition. DTW has been recently applied to uncover the lead-lag associations between energy and agricultural prices by Miljkovic and Vatsa (2023). The alignment between multiple pairs of commodity price time series is generated using the procedures developed by Giorgino (2009) and the DTW-based K-means++ algorithm of Zhang and Hepner (2017). We also describe the advantages, implications, and limitations of using DTW.

This paper has three main findings. First, the lead-lag ordering of the associations between futures and spot prices changed several times, even during short periods. Second, the duration with which futures prices led or lagged cash prices also changed frequently. Third, the method lends itself well to small samples. Several remaining findings and the implications of this research are presented in the concluding section.

2 | LITERATURE REVIEW

Broadly, price discovery refers to how prices are established in markets for a particular transaction (Garcia, 2004). In commodity markets, price discovery often refers to using futures prices for pricing spot market transactions (e.g.,Wiese, 1978). The importance of futures markets to price discovery depends on whether new information is reflected first in futures or spot prices (Garbade & Silber, 1983). Futures prices, in their price discovery role, can be used as reference prices for establishing spot prices and represent market consensus on the expected price in the future based on current information. In general, changes in cash and futures prices will be highly correlated. They depend on the same set of underlying variables (Tomek & Kaiser, 2014).

Arbitrage is crucial for the connections between futures and spot markets. Consider an extreme case when there is no arbitrage because a commodity cannot be easily located and stored. In this case, the spot and futures prices will follow uncoupled random walks. In other words, there will be no tendency for prices in the two markets to come together. The absence of price convergence holds even on the settlement date of the futures contract because the only link between the two markets is arbitrage (e.g., Bekiros & Diks, 2008; Garbade & Silber, 1983).

Thus, in the extreme case where the futures contract will be a poor substitute for a cash market position, prices in one market will have no implications for prices in the other, effectively eliminating the price discovery role of futures markets.

On the other hand, when the supply of arbitrage services is highly elastic, the spot and futures prices will be identical and follow a common random walk. The futures contract will be a perfect substitute for a cash market position, and prices will be *discovered* in both markets simultaneously. In other words, there will be no meaningful distinction between the two markets.

In the intermediate cases, when the elasticity of supply by arbitrageurs is neither perfectly elastic nor zero, prices in the two markets will follow an intertwined random walk. One possibility is that cash prices will move further toward futures prices than futures prices will move toward cash prices, that is, the futures market dominates the cash market. The opposite is also plausible, that is, the cash market could dominate the futures market (Garbade & Silber, 1983). Price discovery, in this case, would be a function of the size of a market. A large futures market, one with a high trade volume and many participants, would be expected to dominate the spot market. Conversely, one may expect the cash market to dominate a relatively small futures market.

Many empirical studies have addressed the price discovery for agricultural commodities. Garcia, (2004) have reviewed these studies comprehensively. Most studies analyzed therein confirmed that futures markets dominated price discovery for both storable and nonstorable agricultural commodities (e.g., Oellermann et al., 1989; Yang et al., 2001). Some empirical studies, however, suggested limiting the ability of the futures markets to transmit price information to cash markets effectively when there is a lack of trading volume and liquidity (e.g., Kuiper, 2002; Maynard et al., 2001). These results are consistent with the aforementioned theoretical models and studies (e.g., Garbade & Silber, 1983). More recently, Dimpfl et al. (2017) have found that cash markets have held sway in the price discovery of agricultural commodities. They concluded that futures contracts contributed less than 10% to price discovery in selected agricultural commodity markets. On the contrary, Adämmer and Bohl (2018) and Penone et al. (2022) showed that futures markets dominated spot markets.

Previous studies on the price discovery role of futures markets in the context of the United States corn markets have relied on more traditional time series methods. Among the most influential studies, Fortenbery and Zapata (1993) employed cointegration to analyze the price discovery process in two proximate local corn markets in North Carolina. They used daily data for corn futures and cash prices in Greenville and Williamston, North Carolina, for period 1980–1991; each year over this period was analyzed separately. They found cointegration in only 4 out of 11 years, with spot price lagging by a period (day). This rather weak finding led them to conclude that the same fundamentals were driving both cash and futures markets for corn. Similarly, Yang et al. (2001) used cointegration and concluded that futures prices for most storable commodities, including corn, in this study (after the FAIR Act) were an unbiased predictor of future cash prices in the long run. It is important to reiterate that neither of these studies nor any other study using time series methods, such as cointegration and Granger causality, investigate, let alone identify, changes in the lead-lag relationship between futures and cash prices. This is something DTW enables us to do.

3 | METHODOLOGY

DTW is a nonparametric pattern recognition method. It contributes most to descriptive data analysis by revealing temporal dynamics between time series and allowing for the assessment of their similarity (e.g., Mastroeni et al., 2021). A comprehensive understanding of the interrelationships between time series is foundational to constructing structural models and ascertaining stylized facts that theories ought to be able to explain. Similar to how machine learning methods can complement conventional econometric models, DTW can complement—and in some contexts replace—the conventional Pearson's correlation coefficient and other similarity measures. DTW can be applied to analyze the similarity between series of varying orders of integration; it is not constrained by the stationarity properties of the data. This is distinctly advantageous over using standard correlation measures applicable to only series that are integrated of order zero. Furthermore, as noted by Raihan (2017), DTW can also be used for forecasting time series.

Fundamentally, DTW minimizes the total distance between observations on two time series. It does so by stretching or compressing the two series locally to make one resemble the other as much as possible. With DTW, one can compute time series alignments by freely mixing a variety of continuity constraints, restriction windows, endpoints, or computations of local distances (e.g., Levenshtein vs. Euclidian distance). The Levenshtein distance is a measure of similarity between two strings. It is defined as the minimum number of changes required to convert string a into string b by inserting, deleting, or replacing a character in string a. Different software packages also provide functions for visualizing alignments and constraints intelligibly. A more technical discussion of DTW follows.

Let the data be structured into $i \in (1, 2)$ time series sequences, commodity futures and cash prices respectively, $p_{i,j}$, in this case, each of length $j \in (1, \ldots, T)$, $p_{1,T} = \{p_{1,1}, p_{1,2}, \ldots, p_{1,T}\}$ and $p_{2,T} = \{p_{2,1}, p_{2,2}, \ldots, p_{2,T}\}$ and compute the elements of the cumulative distance matrix $D_{T\times T}$ as follows:

$$D(1, 1) = d_{1,1}, \tag{1}$$

$$D(1, j) = d_{1,j} + D(1, \quad j - 1), \tag{2}$$

$$D(i, 1) = d_{i,1} + D(i - 1, 1), \tag{3}$$

$$D(i, j) = d_{i,j} + \min\{D(i - 1, \quad j - 1), \quad D(i - 1, \quad j), \quad D(i, \quad j - 1)\}, \tag{4}$$

where $d_{i,j} = \sqrt{(p_{1,i} - p_{2,j})^2}$ is the Euclidian distance between two data points, $p_{1,i}$ and $p_{2,j}$ for $i \in (1, \ldots, T)$ and $j \in (1, \ldots, T)$. DTW aims to find an alignment between p_1 and p_2 that defines an optimal warping path, $W = w_1, w_2, \ldots, w_K$ for $k = 1, \ldots., K$. The elements $D(1, 1)$ and $D(T, T)$ define the starting and ending points of the warping path and represent the opposite corners—the bottom left and the top right corners—of the D matrix. The cumulative matrix is also called the cost matrix, since each element $D(i, j)$ represents the cost to align point i of time series $p_{1,i}$ with the point j of time series $p_{2,j}$. While several warping paths may be computed through the D matrix, we are interested in finding the optimal path that minimizes the total cost of aligning the time series. This is defined as follows:

$$\mathrm{DTW}(p_{1,i}, p_{2,j}) = \mathrm{argmin}_{W=w_1, \ldots, w_K} \sqrt{\sum_{k=1, w_k=(i,j)}^{K} (p_{1,i} - p_{2,j})^2}. \tag{5}$$

Ratanamahatana and Keogh (2004) have proposed several constraints to speed up the computations and accuracy of the algorithm. One of these constraints is not to allow a warping path to drift away from the diagonal elements of matrix D but keep it restricted to a window of size r called the Sakoe-Chiba band (Sakoe & Chiba, 1978). In Equation (5), this constraint translates to $||i - j|| \le r$ for every w_k. A path-dependent normalization is integral to the DTW process (Rakthanmanon et al., 2012; Tormene et al., 2009). In this paper, the alignments between multiple pairs of futures and spot price time series are generated using the *R* package dtw developed by Giorgino (2009).

4 | DATA

Several pairs of corn futures and spot prices are considered to demonstrate this method's ability to account for diverse spatial and temporal aspects of the price discovery process and resulting relationships. The data consist of daily corn prices from DTN Prophet-X. Several time horizons are considered. The first period, which is also the longest, stretches from September 1, 2020, until November 23, 2022. The next period spans 12 months, from September 1, 2021, to August 31, 2022. This is the USDA corn crop marketing year. The USDA marketing year, used as the time period for this analysis, begins 1 month before the typical harvest begins. Corn and soybean harvest is generally in October and November, so the marketing year begins in September. USDA conducts a survey-based inventory of grain in storage on-farm and in commercial storage on September 1 each year. This inventory value is added to expected production (i.e., harvested quantities) and forecasted imports to estimate total supply.

We also identified and analyzed data for two subperiods within the crop marketing year: December 1, 2021, to February 28, 2022, and June 2, 2022, to August 31, 2022. We deemed the first stable and the second turbulent. The turbulent period overlaps with the time of year when corn plants are going through their key reproductive stages and when extreme weather may considerably affect expected yield later in the year. The primary reason for doing this was to demonstrate the capabilities of the DTW method to analyze small samples effectively. Furthermore, splitting the data allowed us to examine the differences in how futures and spot markets interact during periods when prices are volatile and those marked by stable prices.

We chose one elevator location each from Illinois and Nebraska, two major corn-producing states. The two regions encountered different extreme-weather episodes, hence amplifying the potential lead-lag associations and, in turn, price discovery processes. We analyzed the closing futures prices for nearby Chicago Board of Trade corn futures contracts. The contract month and corresponding price switch upon expiry of the current contract. For example, the September corn contract stops trading on the 15th of the month, so the September contract price is reported on September 15. This changes to the December contract price on September 16. Prices are reported in cents per bushel. Finally, spot market prices listed for each elevator are quoted in dollars per bushel and transformed into cents per bushel for the analysis.

In addition to the country elevator spot prices, the lead-lag relationship between the futures prices and the United States corn export elevator prices is also analyzed. To this end, daily free-on-board (FOB) prices for ocean vessels loaded at the United States Gulf and Pacific Northwest (PNW) ports were obtained from AgriCensus. Prices are quoted in United States dollars per metric ton. This analysis is conducted over two periods: the USDA corn crop marketing year, from September 1, 2021, to August 31, 2022, and a shorter period starting on September 1, 2022, and ending on November 10, 2022. We selected the latter for the following reasons.

During the summer of 2022, rainfall within the Mississippi River basin was well below normal. This caused river levels in the Lower Mississippi River to fall more than 11 feet below normal levels, causing significant problems for barge movements of grain into the United States Gulf export terminals. Individual barges could not be filled fully because of draft restrictions. Also, the barge tows (number of barges bundled together and pushed by a single tugboat) had to be shorted (reduced) to increase maneuverability around sand bars and other obstacles and reduce the probability of running aground. This significantly reduced the amount of grain moving into the Gulf terminals and increased the cost of barge movements. Some grain shipments were diverted onto railroads as an alternative. While rail transportation is faster than barges, it is more expensive per bushel (per ton), and many Gulf port terminals have limited rail unloading capacity. They are designed to unload barges quickly and efficiently, not railcars.

5 | RESULTS

We illustrate the results in two ways. The dotted lines in Figures 1, 3, 5, 8, 10, 12, and 14 show the point mapping of the two price series. A vertical point mapping indicates that neither series led or lagged the other, whereas a nonvertical point mapping indicates the presence of a lead-lag relationship. More specifically, lines running from the top right to the bottom left indicate that the series at the top lagged the one at the bottom; dotted lines running from the top left to the bottom right suggest that the former led the latter. Figures 2, 4, 6, 7, 9, 11, 13, and 15 show

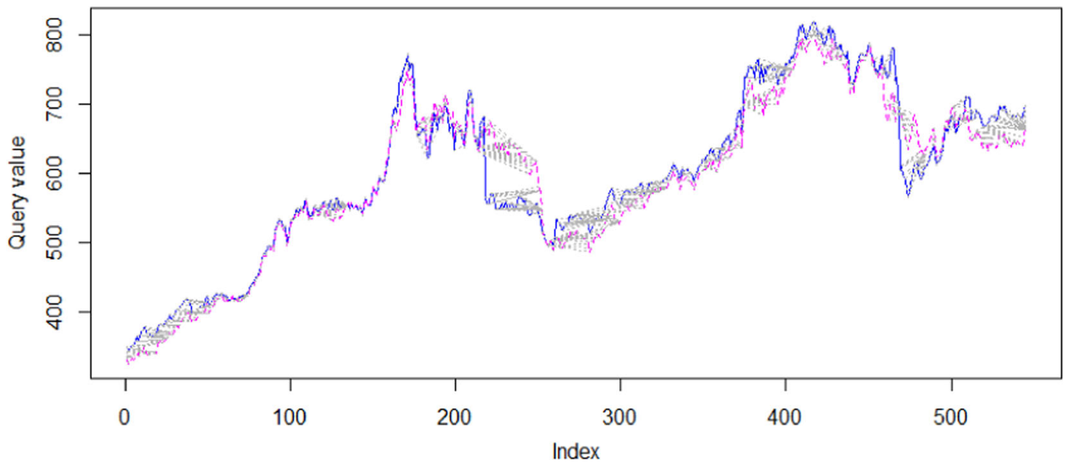

FIGURE 1 Temporal point mapping. Daily futures price of corn (Blue) and cash price in Effingham, IL (Magenta)—September 1, 2020 to November 23, 2022.

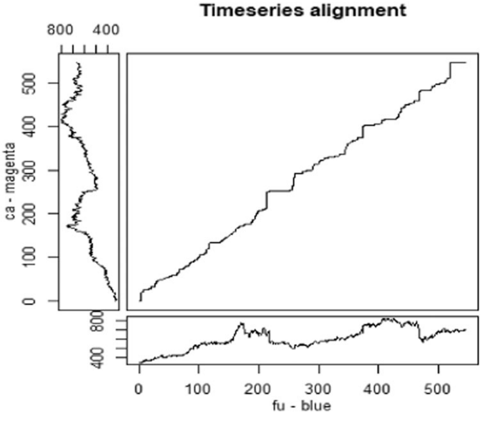

FIGURE 2 Warping path. Daily corn futures price and corn cash price in Effingham, IL—September 1, 2020 to November 23, 2022.

the corresponding distance matrices and the warping paths. Here, a diagonal warping path shows the absence of a lead-lag relationship, while deviations from the diagonal indicate its presence. A rightward deviation of the warping path from the diagonal points to cash prices having led futures prices, whereas deviations to the left of the diagonal suggest the opposite. Finally, a warping path parallel to the diagonal indicates that the duration with which cash prices led (or lagged) futures prices did not change.

Figures 1 and 2 illustrate the lead-lag results for the entire period between September 1, 2020 and November 23, 2022, for Effingham, Illinois; Figures 3 and 4 pertain to the crop marketing year starting September 1, 2021 and ending on August 31, 2022, for Effingham, Illinois. All graphs for both periods suggest that futures markets dominated cash markets, that is, futures corn prices led spot corn prices in Illinois for the most part. However, spot prices led the futures prices intermittently. Figures 2 and 4 also show that the warping path is not parallel to the diagonal; its distance from the diagonal changes, suggesting that the duration of the lead-lag period between the futures and cash corn prices changed over time too.

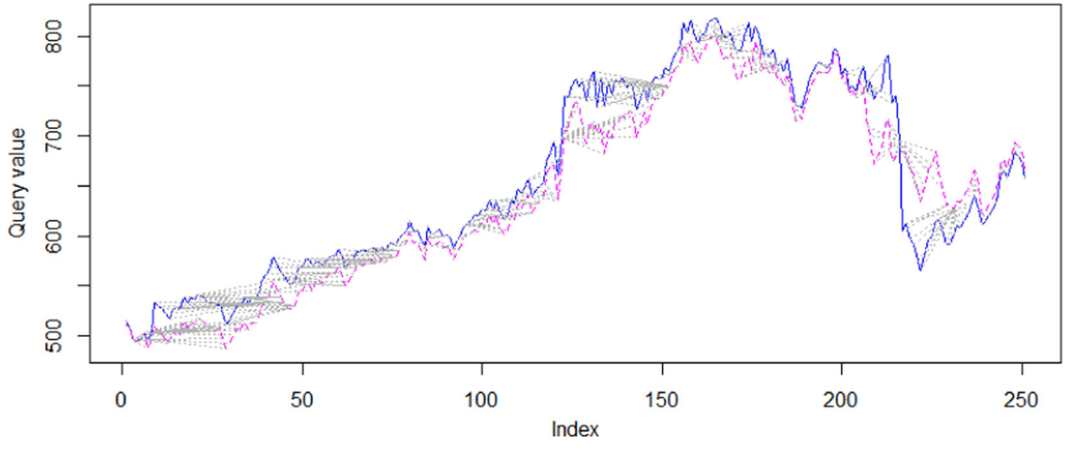

FIGURE 3 Temporal point mapping. Daily futures price of corn (Blue) and cash price in Effingham, IL (Magenta)—September 1, 2021 to August 31, 2022.

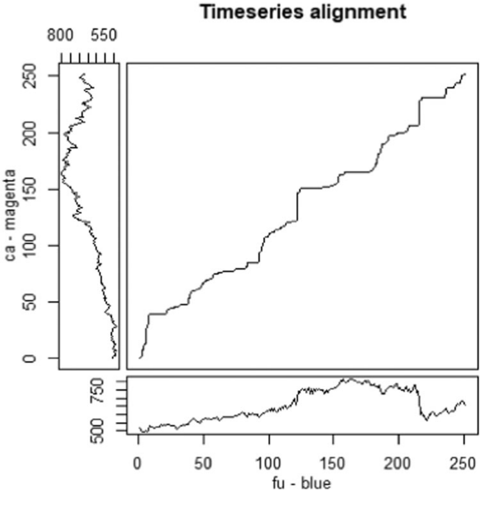

FIGURE 4 Warping path. Daily corn futures price and corn cash price in Effingham, IL—September 1, 2021 to August 31, 2022.

A much more pointed and granular analysis of price discovery is possible by applying DTW to smaller data subsets. Accordingly, we analyzed the lead-lag relationships between futures and spot corn prices in two corn marketing locations during the two periods discussed in Section 4. The summer of 2022 was a rather turbulent period for corn markets. It was hotter and drier than usual in the Western Corn Belt, primarily the states of Nebraska, Iowa, Kansas, South Dakota, North Dakota, and regions of Minnesota, leading to projections of below-average production. We selected Columbus, Nebraska, to represent the region.

In contrast, the Eastern Corn Belt, primarily the states of Illinois, Indiana, Ohio, Wisconsin, and Kentucky, were projected to have above-average production. We chose Effingham, Illinois, to represent the Eastern Corn Belt. The uncertainty regarding weather and crop size impacted both futures and spot prices. However, local spot market prices in the Western Corn Belt were more heavily affected because of uncertainty regarding yields. Hence, spot

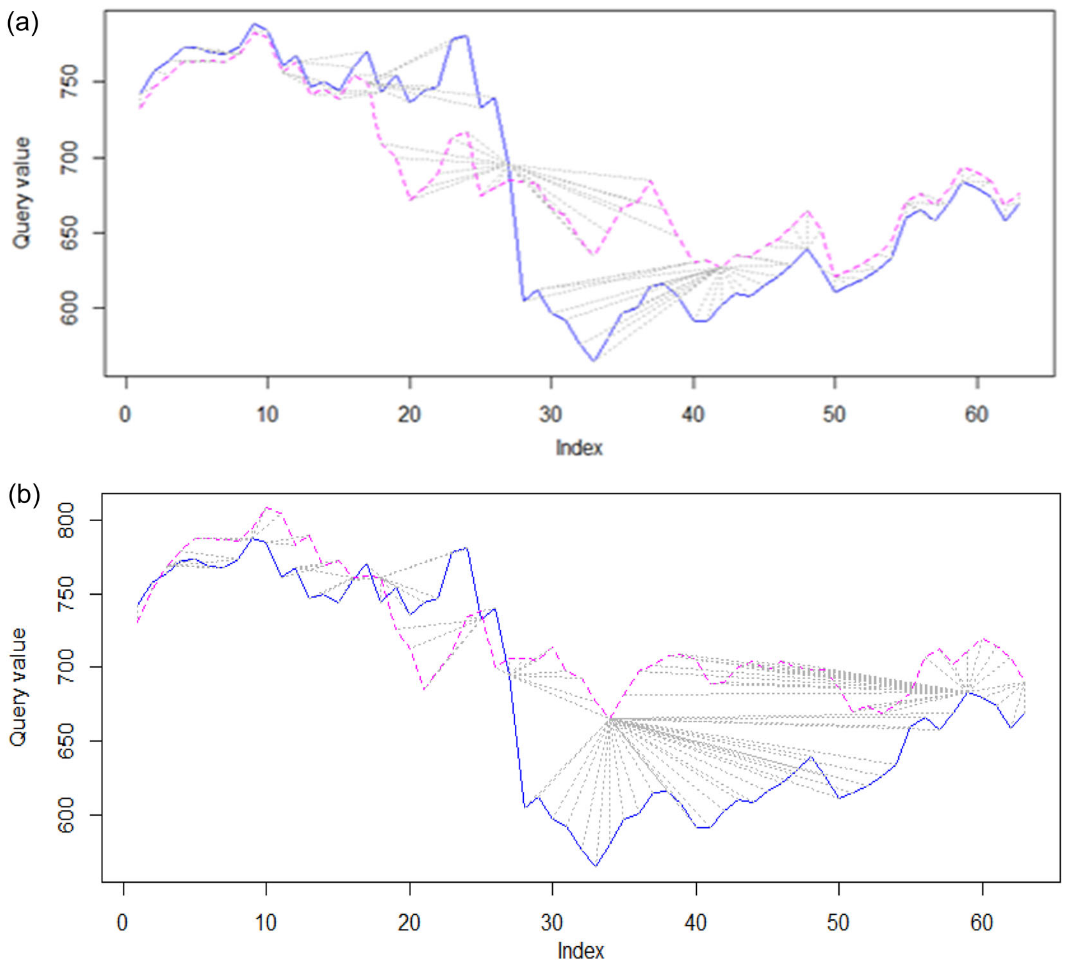

FIGURE 5 Turbulent period: June 2, 2022–August 31, 2022. Temporal point mapping. Daily futures price of corn (Blue) and cash price of corn (Magenta) in: (a) Effingham, IL; (b) Columbus, NE.

prices in Columbus, Nebraska, led the futures corn price for approximately half of that period. As shown in Figures 5b and 6b, spot prices frequently switched from leading to lagging futures prices during this period.

Effingham, Illinois, located in the Eastern Corn Belt, was less impacted by the supply side disturbances than the Nebraska location; this explains why the futures market led price discovery in Effingham (see Figures 5a and 6a). To be clear, the two locations face different demand curves as Illinois serves the domestic agribusiness and ethanol industries and the global markets as it has access through both the riverways and railroads to the corn export locations in the Gulf of Mexico. Producers in Nebraska face more stringent demand constraints as their market is local ethanol and livestock sectors and the PNW export ports, which it accesses via one railroad. These demand-side differences also amplify the dominant role of spot markets during turbulent or uncertain times. Finally, both locations exhibited similar lead-lag behaviors during the stable period (Winter 2021–2022): futures prices led spot prices often in Illinois and throughout the period in Nebraska (see Figures 7a and 7b). Therefore, the futures market fulfilled its price discovery role.

Next, we turn to the relationship between the futures corn prices and export elevator prices during the 2021–2022 USDA marketing year, first for the Gulf and then for the PNW. Figures 8 and 9 show that futures prices led Gulf prices from September 2021 until the beginning of April 2022. The duration with which futures prices led

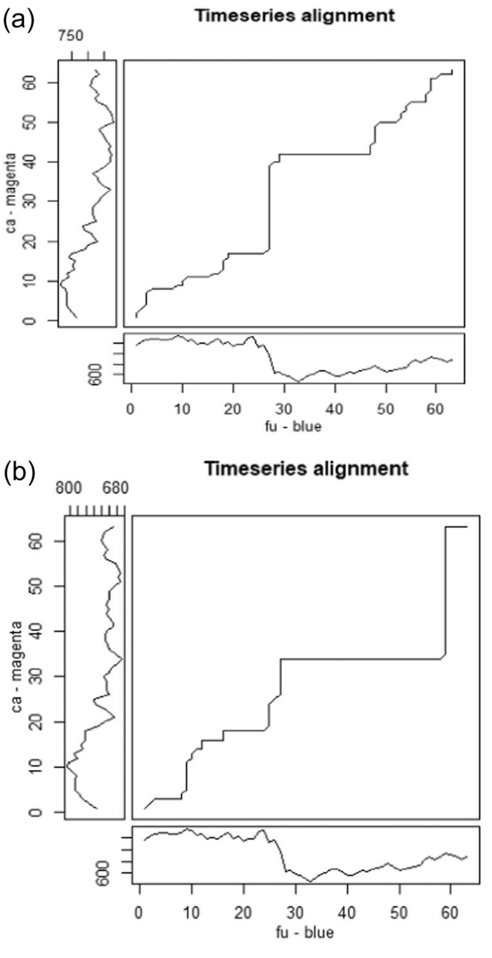

FIGURE 6 Turbulent period: June 2, 2022 to August 31, 2022. Warping path. Daily futures price of corn (Blue) and cash price of corn (Magenta) in: (a) Effingham, IL; (b) Columbus, NE.

increased until December/January and then decreased. Gulf prices led futures price from April 2022 until approximately July 20, 2022, when the relationship reversed. A detailed explanation of these lead-lag relationships follows.

From September through April 1, the futures market performs one of its primary functions by signaling the allocation of supplies across time (i.e., carry in the market). The cash market at the Gulf export terminals uses the information in the futures market to establish cash bid prices (futures lead cash). However, on March 31, the USDA releases the Perspective Plantings report, which estimates planted acreage by crop at the state and national levels. This annual report surveys approximately 72,900 farmers in the United States, asking how many acres of each crop they intend to plant that year. The 2022 report indicated that farmers intended to plant less corn and more soybeans than expected. This created a shock in the market, which increased the value of both the old crop produced in 2021 and the new crop expected to be produced in 2022. In addition, the Brazilian Safrinha corn crop, which accounts for about 70% of Brazil's total corn production and a significant amount of its exportable stocks, is not ready for harvest until late May or early June. This means that the United States is the primary source for large quantities of corn exports at this time. Historically, the United States has been the largest exporter of corn, with Brazil being the second-largest exporter. During the 2022–2023 marketing year, Brazil surpassed the United

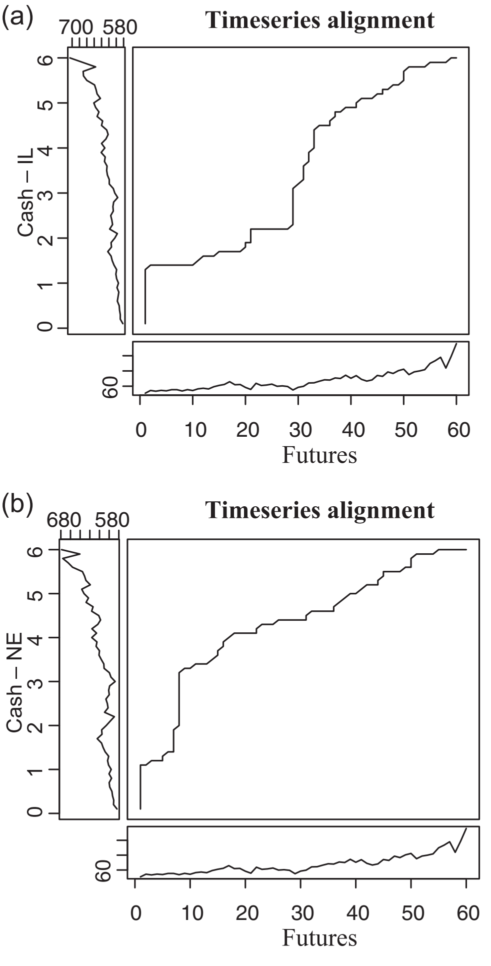

FIGURE 7 Stable period: December 1, 2021 to February 28, 2022. Warping path. Daily futures price of corn (Blue) and cash price of corn (Magenta) in: (a) Effingham, IL; (b) Columbus, NE.

States as the largest corn exporter. Our hypothesis is that international corn buyers became nervous and began buying more United States corn after the *Perspective Plantings* report, and the cash market at the Gulf export terminals reflected those purchases.[1] Following this logic, by mid-July, the uncertainty regarding the size of the United States and Brazilian Safrinha corn crops fell. As noted above, the Brazilian Safrinha crop is typically harvested in early June, so global corn buyers have a “new” source for their needs, and it is more difficult for the United States corn exporters to compete. Also, more accurate yield projections for the United States corn become available in early August. The export elevators in the Gulf did not have to bid as aggressively for domestic corn supplies and began *following* the futures market price trends as the United States corn harvest approached.

Figures 10 and 11 show the associations for the PNW. Futures prices led PNW prices from September 1, 2021, until mid-to-early June (approximately June 6) 2022. The lead period increased until mid-January and then decreased. PNW prices led futures prices from late May until mid-July (July 18–20); the relationship reversed at that time for approximately the last 50 days.

[1]Please note that purchases can be for both immediate and deferred delivery.

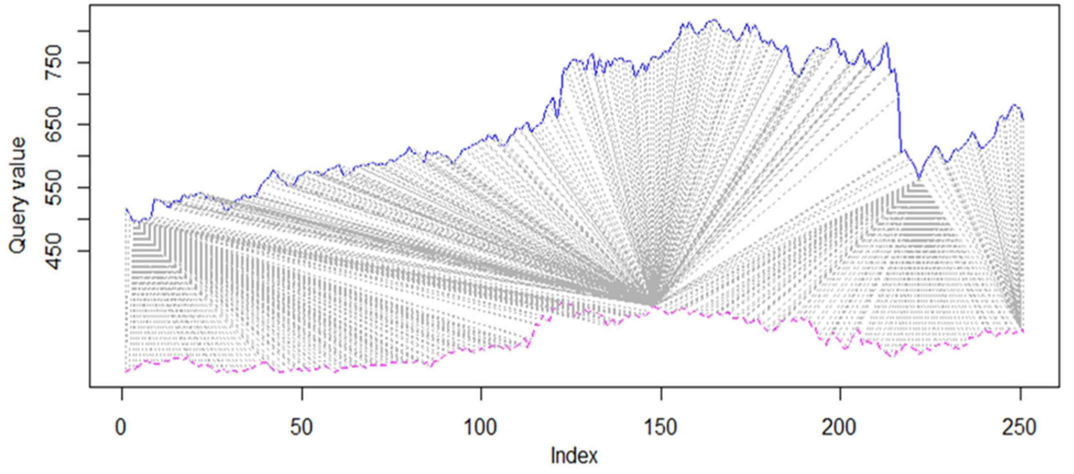

FIGURE 8 Temporal point mapping. Daily corn futures (Blue) and Gulf of Mexico price (Magenta) for the marketing year September 1, 2021–August 31, 2022.

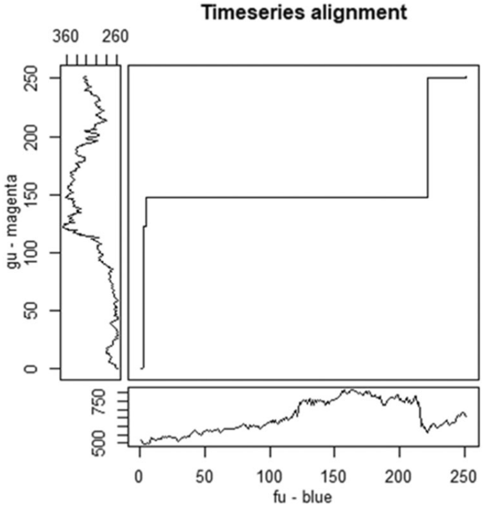

FIGURE 9 Warping path. Daily corn futures (Blue) and Gulf of Mexico price (Magenta) for the marketing year September 1, 2021–August 31, 2022.

During the 2022 calendar year, approximately 20% of all United States corn exports went through the PNW export facilities.[2] Our hypothesis is that the same underlying cash and futures market conditions that impacted the United States Gulf cash prices also impacted the PNW cash prices. However, because the PNW export facilities handle fewer bushels of corn, it took longer for PNW cash prices to respond in the spring. The export window lasted a little longer in the PNW because China purchased United States corn later in the season. It is typically less

[2]In contrast, approximately 60% of the corn exports went through the Mississippi Gulf (i.e., New Orleans). About 18% of the corn exports went through "interior" facilities. These "interior" facilities are often large grain elevators that ship corn into Mexico by rail.

During the 2021/22 marketing year, Mexico was the largest buyer of United States corn with 16.7 million metric tons (27.9% of all exports), China was second with 14.3 million metric tons (24.0%), and Japan was third with 10.2 million metric tons (17.0%).

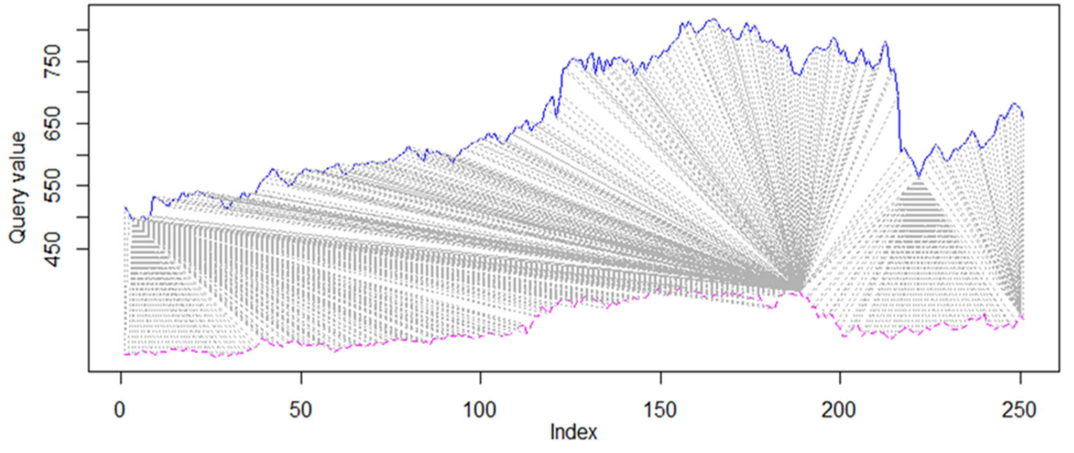

FIGURE 10 Temporal point mapping. Daily corn futures (Blue) and PNW price (Magenta) for the marketing year September 1, 2021–August 31, 2022.

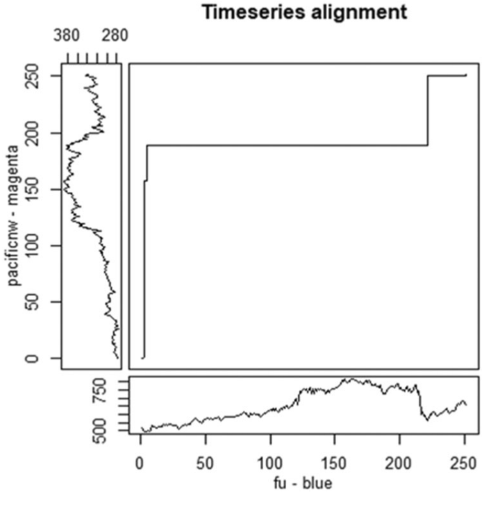

FIGURE 11 Warping path. Daily corn futures (Blue) and PNW price (Magenta) for the marketing year September 1, 2021–August 31, 2022.

expensive to ship United States grain into China through the PNW relative to the Gulf because of the shorter distance.[3]

Next, we present the lead-lag results for the corn futures and United States Gulf prices during the restricted period, September 1, 2022 to November 10, 2022, as described in Section 4. As shown in Figures 12 and 13, futures price led the Gulf price for 22 business days, that is, until October 4, 2022. The largest lead duration was around September 17. After October 4, the futures price lagged the Gulf price. An explanation of these results follows.

[3]Also note that most of the United States grain shipped to China from the United States Gulf does not go through the Panama Canal because of the Canal's fees. The vessels loaded in the United States Gulf most often transit past South Africa, through the Indian Ocean and South China Sea, to ports along the Eastern coast of China.

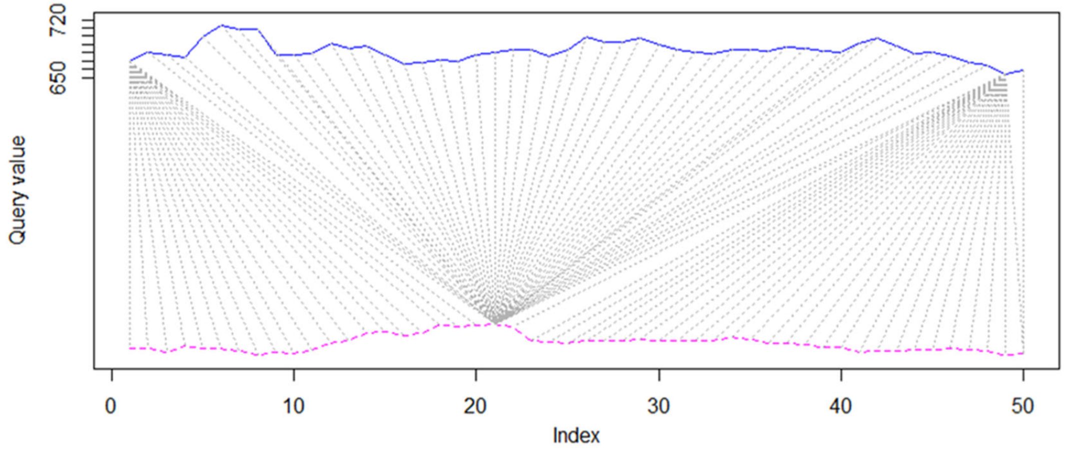

FIGURE 12 Temporal point mapping. Daily corn futures (Blue) and Gulf of Mexico price (Magenta) for the period September 1, 2022–November 10, 2022.

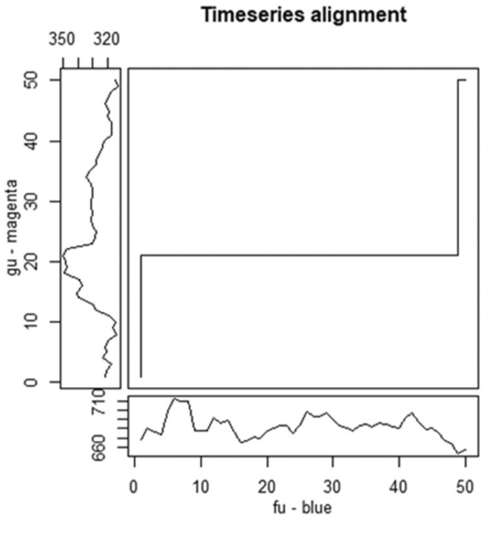

FIGURE 13 Warping path. Daily corn futures (Blue) and Gulf of Mexico price (Magenta) for the period September 1, 2022–November 10, 2022.

Barge shipping volumes on the Lower Mississippi River typically begin falling in August, as export sales fall seasonally and the grain delivery systems get ready for corn and soybean harvest. Shipping volumes start increasing in October as harvest grain flows increase, increasing barge rates. However, in the fall of 2022, barge rates surged because of low water levels and reduced shipping capacity. Barge rates went from a 3-year average index rate of 515 to 2428 (October 4, 2022, values for Cairo-Memphis loading to the United States Gulf). This equates to an increase from $16.17/short ton to $76.24/short ton. In contrast, shuttle train tariff rates from Champaign-Urbana to New Orleans were $42.91/short ton at that time. Barge rates peaked during the week of October 11. Shipping volumes and rates did not return to normal until mid-January. Gulf export terminals were scrambling for grain supplies because the ocean vessels were scheduled to arrive, and buyers were expecting their shipments. In addition, the exporter must pay demerge penalties if the ocean vessel waits more than 3 days. Some export

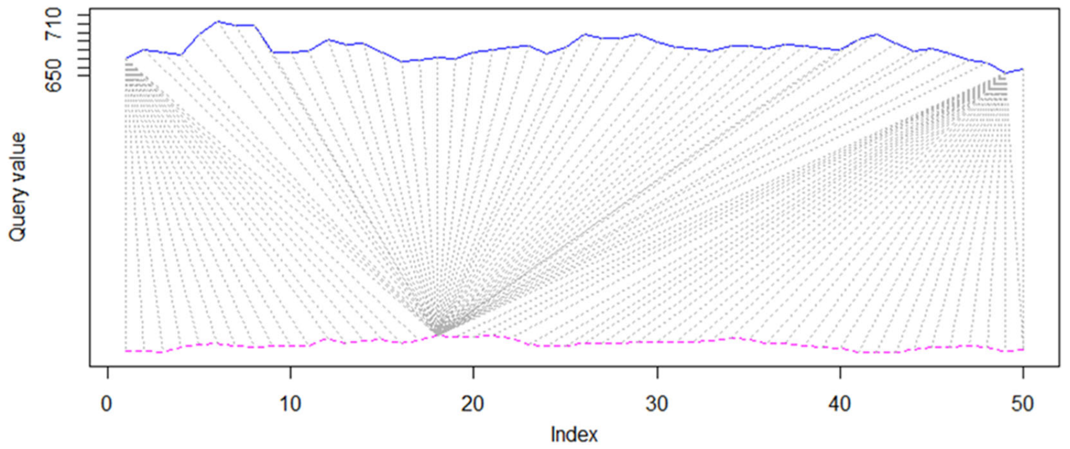

FIGURE 14 Temporal point mapping. Daily corn futures (Blue) and PNW price (Magenta) for the period September 1, 2022–November 10, 2022.

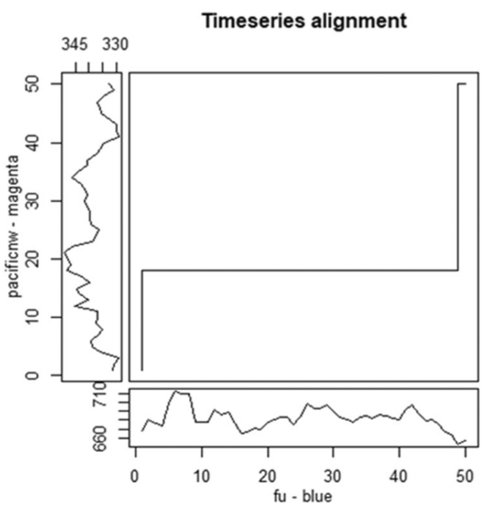

FIGURE 15 Warping path. Daily corn futures (Blue) and PNW price (Magenta) for the period: September 1, 2022–November 10, 2022.

terminals supplemented barge deliveries with rail deliveries. Others shifted vessel loading from the Mississippi Gulf terminals (New Orleans) to the Texas Gulf terminals (Galveston and Houston). However, the Texas Gulf terminals are not as large. Eventually, some loadings and vessels were diverted to the PNW export terminals.

In summary, the cash prices for corn delivered to the United States Gulf separated from the futures market. Once again, the futures market is only concerned about regulating grain flow at a national level over time. The cash market, at a specific location, must regulate grain flow over time and space.

Finally, we look into the lead-lag relationship between the corn futures and the PNW price. As presented in Figures 14 and 15, the futures price led the PNW price for 18 business days, that is, until September 28, 2022. The largest lead was around September 15; after September 28, the futures price lagged the PNW price. Because the Lower Mississippi River barge issues began developing before the peak of harvest, a few corn shipments were diverted to the PNW export terminal loading. This unexpected increase in corn shipments through the PNW caused the cash market prices to separate themselves from the futures market. Also, no one knew how long the river levels would remain low and cause problems for barge shipping. Rains did occur in the Mid and Upper Mississippi basin, which improved shipping flows, but it took several months of additional rain for the river levels to return to normal.

6 | CONCLUDING REMARKS

We utilized DTW, a nonparametric pattern recognition technique, to analyze the associations between corn futures and spot markets in the United States. The results showed that futures markets have been critical to price discovery in the export elevators at both the Gulf and PNW locations. Nevertheless, spot markets have dominated futures markets intermittently. Methodologically, we demonstrated the several advantages of using DTW. First, DTW can detect period-to-period changes in lead-lag associations between futures and cash market price series. This provides granular insights into their dynamic interlinkages, as the temporal alignment is not fixed, which aligns with practical realities. Second, the method is independent of the stationarity properties of the time series in question, eliminating the need to extract the stationary components using decomposition techniques or differencing the time series to achieve stationarity. Third, the method lends itself well to small samples, which econometricians contend with routinely. Although corn markets appear to be well integrated over longer periods, there is considerable slippage between cash and futures markets over shorter time intervals. DTW is well-suited to examining the differences in price discovery between different cash markets during such intervals. The method also captures the differences in price discovery across different stages in the supply chain. Lastly, the changes in the lead-lag associations are presented intelligibly using intuitive visualizations.

From a practical standpoint, the capability of this method to yield detailed insights into the dynamics of lead-lag relationships, including variations in the number of leading periods over time, offers significant value to traders, investors, and speculators. It enables them to pinpoint specific moments and the events that triggered shifts in price correlations, thereby enhancing their ability to forecast future changes under similar market conditions and external influences. Unlike traditional time series analyses, which are constrained to identifying a singular lead-lag relationship for any given timeframe—a quite improbable scenario given the commodity price dynamics—DTW allows and can help identify variations in the relationships. DTW also overcomes the limitations of parametric techniques criticized for their inadequacy in analyzing brief periods with a few data points, presenting a clear advantage in analyzing small samples.

Employing DTW to analyze price discovery could also yield valuable insights for policymakers. DTW has the potential to ascertain whether general or commodity-specific policy measures alter the interplay between futures and spot prices at particular locations; it can also gauge whether the impact of policy is transitory or persistent. Although parametric time series methods, like cointegration analysis and vector autoregression, might offer similar insights, the finer details and nuances of the findings could be obscured due to the inherent limitations of parametric analysis.

The most immediate and apparent future research on the topic would be to conduct comparative studies on price discovery in corn and other storable commodity markets using DTW and compare the results with those from traditional time series techniques. This would be especially useful when using smaller data sets and shorter periods, possibly with higher frequency data. Another interesting application of the DTW method would be in thinner markets with lower trading frequency. Theory suggests that futures markets for such commodities would play a lesser role in the price discovery process. A corn-related market of interest would be ethanol, characterized by relatively few trades and contracts compared to corn, soybeans, wheat, or most other traditional agricultural storable commodities.

While DTW provides several advantages in studying price interrelationships, there are some limitations to using this method. First, if these interrelationships, including price discovery, are to be studied in a more complex, multivariate framework, it would be difficult to include the results of DTW analysis in such models. Nevertheless, DTW could be used to complement multivariate analysis conducted using traditional techniques such as vector autoregression and error correction models by pointing to periods marked by stable or unstable relationships between pairs of prices. Second, if long periods (e.g., several decades) with long time series are available, using traditional time series methods may be more appropriate as some important features of corn and other agricultural markets, such as seasonality, trends, and cycles, could be more readily considered in them.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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