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SHIFTING PRICE DISCOVERY IN LOCAL SOYBEAN MARKETS: EVIDENCE FROM THE TRADE WAR PERIOD

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SHIFTING PRICE DISCOVERY IN LOCAL SOYBEAN MARKETS: EVIDENCE FROM THE TRADE WAR PERIOD

Practitioner's Abstract

This paper examines how price discovery between soybean crushing plants and river terminals evolved across three price regimes defined by the 2018–2020 US-China Trade War. Using daily cash prices from 37 crushing plants and 81 river terminals across Ohio, Indiana, Illinois, Minnesota, Iowa, and Missouri, we estimate which type of local buyer leads price adjustments in Midwestern soybean markets. We find that price discovery shifted from crushing plants toward river terminals over the study period, with the largest shift occurring after the trade war. Crushing plants have become persistent and less price-reactive buyers due to steady demand from the renewable diesel boom. River terminals, which are exposed to increasingly volatile global export demand, now lead local price adjustments.

During the US-China Trade War, all cash prices lost their long-run relationship with nearby futures prices. The loss of long-run price relationships suggests that hedging with soybean futures may have been less effective and more volatile during the trade war, as the cash-futures relationship was disrupted. Following the trade war, the contribution of nearby futures to local price discovery declined, indicating that local delivery points are playing a larger role in price formation. The decrease in price discovery from futures markets coincides with a reduction in daily futures trading volume. These findings have implications for producers, grain merchandisers, and risk managers who rely on local price signals and futures markets for marketing and hedging decisions.

Key words: price discovery, soybean markets, 2018–2020 US-China Trade War, river terminals, crushing plants

1 Introduction

Over 90 percent of the US soybean supply is destined for domestic crush or export (USDA ERS, 2026). However, the relative contributions of crush and export demand to US soybean usage vary with global disruptions and policy shocks. The 2018–2020 US-China Trade War reduced the total exports of US soybeans by 21 percent in 2018 relative to the previous five years (Cowley, 2020). On the other hand, soybean crush volume has increased year over year in 12 of 13 years between the 2013/2014 and 2025/2026 marketing years (USDA ERS, 2026), in part due to increased demand for renewable diesel (O'Neil, 2024; Wang and Janzen, 2025). Soybean prices rely on demand from these two sources. At the onset of the US-China Trade War, US soybean prices fell by 20 percent between April and September of 2018 (Cowley, 2020).

In local soybean markets, crush and export demand are represented by crushing plants, which process soybeans on-site, and by river terminals, which transport soybeans by barge to ports for export. While crushing plants and river terminals have positive effects on local prices (McKenzie, 2005; Mitchell and Biram, 2025; Wu et al., 2025), it is unclear how they jointly shape local pricing dynamics. Moreover, given shifting demand due to trade disruptions and crush expansion, we expect local buyers' contribution to price discovery to vary across price regimes. Therefore, we seek to determine who leads price adjustments in local markets and how that has shifted across three price regimes, underpinned by trade disruptions and crush expansion. Specifically, how has local soybean price discovery evolved between export-oriented river terminals and domestic soybean crushing plants during the 2018–2020 US-China Trade War and the continued expansion of crushing capacity?

We use 37 soybean crushing plants and 81 river terminals across Ohio, Indiana, Illinois, Minnesota, Iowa, and Missouri to calculate the New Leadership Share (NLS) of Lien et al. (2025) and the PILS[4] of Shen et al. (2025). Since futures prices contribute significantly to price discovery (Arnade and Hoffman, 2015), nearby futures prices were also included in the analysis. Our analysis covers three price regimes from 2016 to 2023 based on identified structural breaks in the mean price of nearby soybean futures: April 18, 2016, to June 11, 2018 (pre-trade war), June 12, 2018, to December 13, 2020 (trade war), and December 14, 2020, to September 13, 2023 (post-trade war). Our primary specification relies on the data-driven breakpoint on December 13, 2020, to end the trade war. While this is well after the signing of the Phase 1 Trade Agreement, it represents the return to pre-trade-war price levels and global pricing patterns (Adjemian et al., 2021).

Prior research has established that soybean crushing plants and river terminals have significant local price effects on soybeans. There is evidence that crushing plants positively affect the local soybean basis, calculated as cash prices minus futures prices (Wu et al., 2025). Additionally, disturbances along the Mississippi River, such as shocks in barge rates or low river levels, negatively affect the soybean basis (McKenzie, 2005; Mitchell and Biram, 2025). Due to the river terminals' role in transporting soybeans for export, the US-China trade war has also been shown to weaken soybean basis along the Mississippi River (Adjemian et al., 2019). However, the local price effects of the trade war across the Midwest are mixed (Adjemian et al., 2019).

Functioning crushing plants and river terminals are known to have positive effects on local prices. However, no prior research has quantified the relative contribution of crushing plants and river terminals to local price discovery, or how price discovery has shifted in response to trade policy and demand shocks. Using price discovery measures, we seek to build on the known price effects of local buyers to understand how these effects interact in the evolution of local market prices. We hypothesize that river terminals' contribution to price discovery will increase relative to that of crushing plants, as crushing plants maintain persistent demand, whereas river terminals respond to volatile global demand.

We make three contributions to the literature. First, this is the first application of the NLS and PILS price discovery measures to agricultural commodity prices. The price discovery measures are suitable for multivariate analysis and allow for estimating local cash price discovery while controlling for the contribution of futures prices.

[4] Shen et al. (2025) do not formally define the PILS acronym

Second, this is the first documentation of a complete but temporary loss of cash-futures cointegration in crop prices. We find that all soybean cash prices lost cointegration with nearby futures prices during the trade-war period, a period characterized by low cash prices and low realized volatility in cash prices and basis. We find that while low realized volatility in the basis indicates steady basis trends, cash prices did not maintain a long-run equilibrium with futures during the trade war. The implications for soybean producers and buyers may include increased hedging risk during market disruptions.

Third, we determine that soybean price discovery has decreased at local crush plants and increased at river terminals in six Midwestern states with river access (Ohio, Indiana, Illinois, Minnesota, Iowa, and Missouri). The largest shift in price discovery occurred after the trade war. In the bivariate analysis, the mean crushing plant price discovery decreased by 4–8 percentage points between the trade-war and post-trade-war periods, depending on the sample. Mean river terminal price discovery increased by 4–8 percentage points between the trade-war and post-trade-war periods across four subsamples of cointegrated markets. Our findings are consistent with crushing plants becoming persistent buyers of soybeans. Their persistent demand has slowed their integration of market information into their pricing decisions. Meanwhile, river terminals, which rely on global markets, are exerting greater influence on local price dynamics.

2 Background

Between 2012 and 2018, US soybean production increased annually (USDA ERS, 2026). Soybean usage to keep up with growing production is largely driven by two demand markets: soybean exports and domestic crushed soybeans. Figure 1 shows the evolution of soybean production, domestic crushing, and exports between the 2012/2013 and 2025/2026 marketing years. Between 2012 and 2016, both soybean exports and crushing increased, in line with rising production. However, in June 2018, China announced retaliatory tariffs on US goods, including soybeans. During the 2017/2018 marketing year, US soybean exports fell by 2 percent. In the two full marketing years following the tariffs, there were decreases of 18 percent and 4 percent. Following the Phase 1 Trade Agreement, US soybean exports reached a record high in the 2020/2021 marketing year (USDA ERS, 2026). However, exports decreased in four of the five years between 2021/2022 and 2025/2026.

On the other hand, soybean crush volume has continued to grow. From marking year 2012/2013 through 2024/2025, annual soybean crush volume decreased in only one year, evident from Figure 1. In the 2025/2026 marketing year, domestic crushing is forecast to account for 56 percent of the US soybean supply, the largest share since the 2003/2004 marketing year (USDA ERS, 2026). The increase in soybean crush volume is consistent with rising demand driven by the renewable diesel boom. Between 2015 and 2023, production of renewable biomass-based diesel doubled (Swanson et al., 2024).

Since 2015, the share of soybean oil used for biofuel has doubled (Swanson et al., 2024), with most

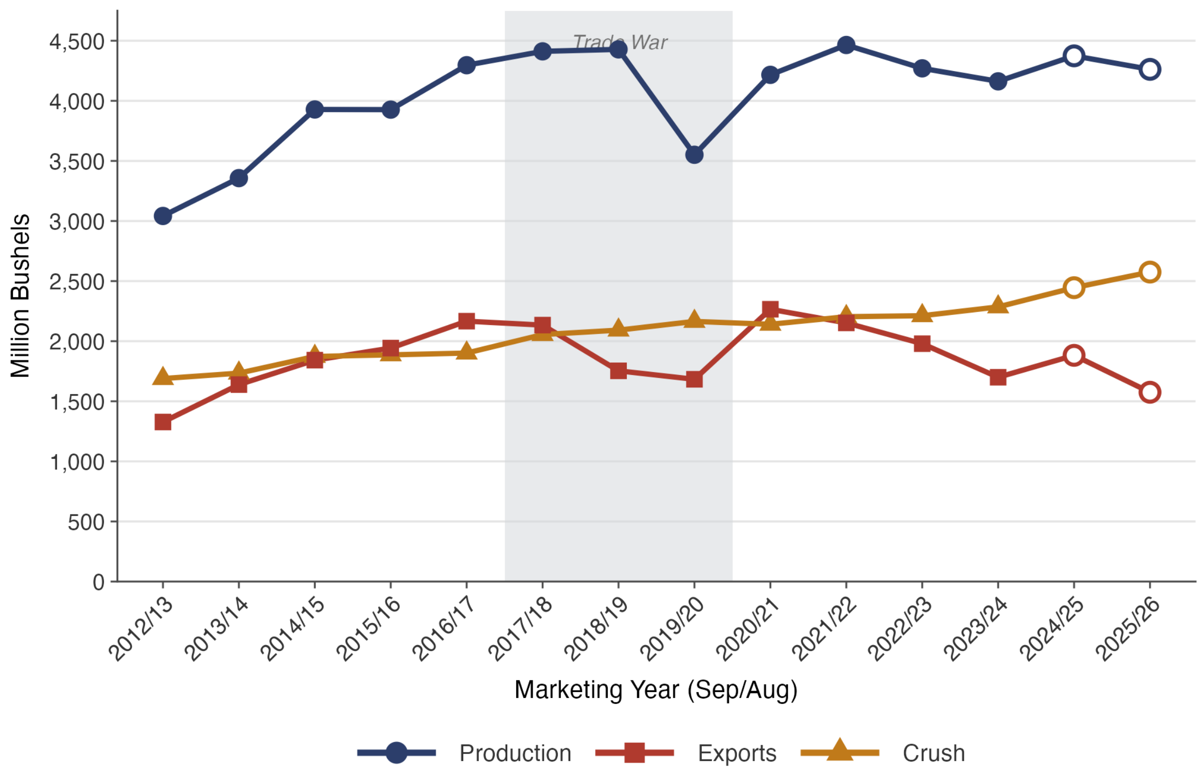

Figure 1: Marketing year soybean production, exports, and crush in millions of bushels from 2012/2013 to 2025/2026. 2024/2025 data is an estimate, and 2025/2026 data is a forecast. Data Source: USDA ERS (2026).

of the expansion coming after 2021 (Wu et al., 2025). Before the renewable diesel boom, soybean meal was the economic driver of soybean crushing; however, recent trade and oil-extraction trends indicate that oil demand is driving expansion in soybean crush volume. Oil extraction rates from soybeans have been above the 60-year trend since the 2020/2021 marketing year (Wang and Janzen, 2025). Additionally, soybean oil exports have decreased while soybean meal exports have increased, indicating a shift in domestic demand for the two products (O'Neil, 2024; USDA Foreign Agricultural Service, 2023).

2.1 Local Price Effects

In local markets, crush demand is represented by soybean crushing plants, and river terminals represent export demand. In local markets, crushing plants and river terminals positively affect soybean prices. Wu et al. (2025) show that crushing plants increase the basis by over \$0.10/bu with diminishing increases spatially. When river terminals face exogenous shocks that reduce their access to global markets, local prices decline. Mitchell and Biram (2025) show that low river levels have a negative price effect that is most significant at river markets and is transmitted inland. Additionally, shocks to barge rates increase the cost of moving soybeans downriver to export terminals, and the price effect is transmitted inland from the river (McKenzie, 2005). The shock decreased basis at a river terminal and a soybean crushing plant, but the effect was more pronounced at the river terminal.

In addition to physical or domestic factors, global market shocks also influence US soybean prices. When China announced retaliatory tariffs for US soybeans in June 2018, US soybean futures plummeted. Figure 2 shows the nearby soybean futures prices for the marketing year leading into and through the trade war delineated by China's announcement of retaliatory tariffs. While the Phase 1 Trade Agreement was signed on January 15, 2020, it was not until the fall of 2020 that futures prices returned to pre-trade-war levels. The price shock did not affect all local markets equally. Markets more reliant on exports, such as those along US rivers from where river terminals move soybeans to ports, experienced more negative effects (Adjemian et al., 2019, 2021).

2.2 Market Integration

In analyzing barge shocks, McKenzie (2005) identified three markets (Gulf, Memphis, and Little Rock) in which price shocks were transmitted. Lewis et al. (2012) provide further evidence of price relationships across soybean markets using vector auto-regressions (VARs) and Granger Causality tests for 13 soybean markets across the US. Lewis et al. (2012) find simultaneous causality between the soybean crushing plant and river terminals in their analysis. While the VAR approach of Lewis et al. (2012) demonstrates simultaneous causality, it does not directly address long-run cointegration. Goodwin and Piggott (2001) evaluate the cointegration of local soybean markets in North Carolina using pairwise comparisons of three soybean markets to a central fourth market. The results indicate that the spatially nearby markets are cointegrated and maintain a long-term

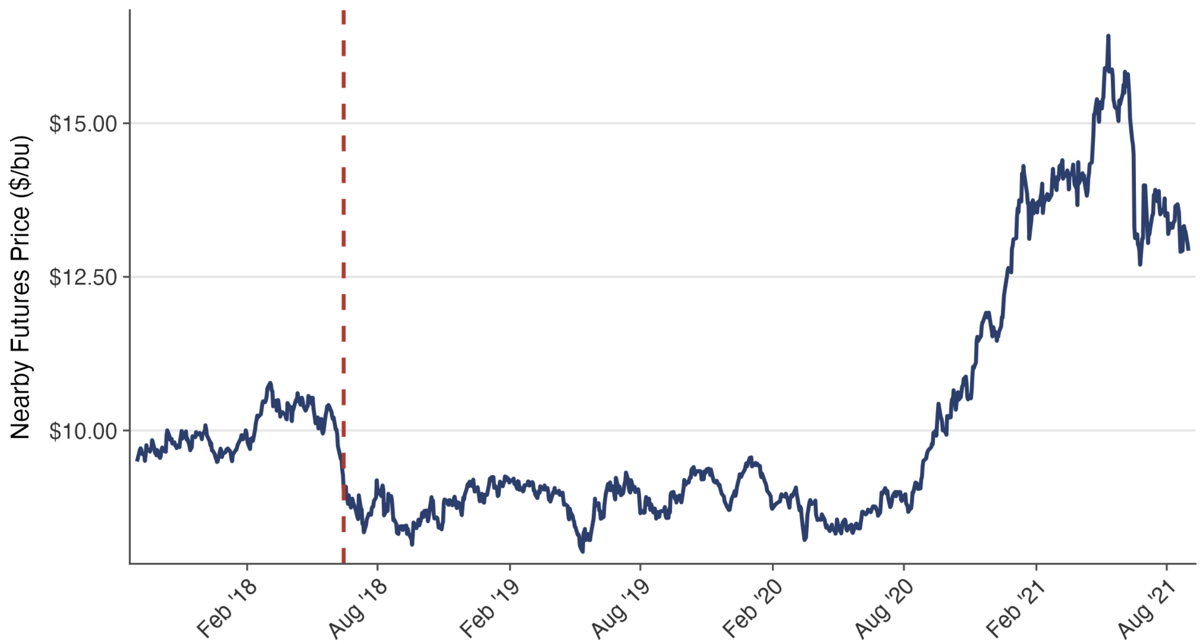

Figure 2: Nearby soybean futures for 2017/2018–2020/2021 marketing years delineated by the June 15, 2018, Chinese retaliatory tariff announcement. Data Source: DTN (2025)

relationship.

2.3 Price Discovery

In the presence of cointegrating time series, price discovery, described informally as “who moves first,” can be estimated (Putniņš, 2013). In the past ten years, price discovery measures have been used across agricultural markets. Price discovery is not static. Arnade and Hoffman (2015) use a measure of price discovery to determine if soybean cash or futures prices are where prices are discovered. Arnade and Hoffman (2015) find that the share of price discovery in futures markets has increased over time. However, cash prices accounted for 42 percent of price discovery between 2005 and 2013. Janzen and Adjemian (2017) show that wheat price discovery in the global market differed before and after 2010, as indicated by a t-test of differences in the daily information leadership share. Hu et al. (2020) use information leadership share to determine price discovery in corn and cattle markets from nearby and deferred futures contracts. They find that price discovery shifts to deferred contracts as trading volume shifts there.

From previous research, four things are clear. First, over the past ten years, the US soybean market has undergone significant changes. Soybean crush volume has continued to expand while export markets have become volatile. Second, local access to crushing or export markets has been shown to positively impact prices. Third, cointegration among local markets means that prices from crushing plants and river terminals are transmitted to buyers across markets. When multiple price series are cointegrated, we can determine how each contributes to market price discovery. Fourth, price discovery is not static. Changes in price regimes, whether due to policy changes or market shocks, can alter the location of price discovery. Drawing on these four observations, this research seeks to consolidate these threads of research. We explore how local soybean price discovery has evolved between river terminals (export demand) and crushing plants (domestic crush demand) across three price regimes characterized by volatile exports and rising crush demand.

3 Empirical Method

We explore the trends in local soybean price discovery during three price regimes characterized by trade volatility and increased domestic crush expansion. Therefore, we must first define the pre-trade-war, trade-war, and post-trade-war periods. We employ a data-driven approach to identify appropriate breakpoints in soybean prices that may be associated with changes in global soybean markets. Specifically, we utilize a Bayesian Information Criterion (BIC) based structural break test of Yao (1988) to identify the ideal number and location of breaks in the mean nearby soybean futures. We choose to identify structural breaks using futures rather than independent cash prices to ensure uniform periods across all market combinations.

Once we determine the pre-trade-war, trade-war, and post-trade-war periods, we calculate price discovery measures by estimating vector error correction models (VECMs) for the market combination. However, a VECM is appropriate only when the price series are nonstationary and cointegrated I(1). Therefore, we employ a multistep approach. First, we drop all cash price series that are missing more than 15 percent of trading-day observations in any given period. Second, we fill the remaining missing observations using linear interpolation. The cleaning process is run for each cash price series in each period independently. We also run the data filtering process with 10-percent and 20-percent missing-observation thresholds and use cubic-spline imputation for robustness. The results of the robustness checks are reported in Appendix A.

Since VECM estimation requires I(1) price series, Augmented Dickey-Fuller tests with trend and constant components were conducted for each price series in each period using the most general specification. Any location-period combination where the null hypothesis of a unit root was rejected at the 0.05 significance level was removed. Next, we determine the optimal number of lags for each market combination based on BIC. The BIC was chosen for lag selection because it tends to favor more parsimonious models, particularly given the large number of VECMs to estimate. AIC robustness is reported in Appendix A.

Finally, with the remaining nonstationary price series, we check for cointegration between the crush plant and river terminal combinations. Cointegration tests were done on a pairwise basis and in a trivariate setting, including nearby futures, since futures prices contribute significantly to price discovery. To determine cointegration, we use the maximum eigenvalue statistic from Johansen's rank tests with constants in the cointegrating space for the pairs and trivariate combinations (Johansen and Juselius, 1990). The number of cointegrating relationships between a set of price series determines the cointegration rank. Price discovery measures rely on a single stochastic trend and statistical significance at the 0.05 level. Therefore, in the bivariate case, the price series must be cointegrated of rank 1, and in the trivariate case, of rank 2. Although the magnitude is much greater than in previous research, these pairwise and multivariate comparisons are similar to the procedures used by Lewis et al. (2012) and Goodwin and Piggott (2001).

3.1 Estimating Price Discovery

Common price discovery measures have evolved over the past 30 years. Two frequently employed methodologies are the component share (CS) and information share (IS). Hasbrouck (1995) defined IS as a market's contribution to the efficient price innovation variance. Gonzalo and Granger (1995) identified common factor weights that explain each market's contribution to permanently moving the market price. The CS measure is based on the principle of markets with increased common factor weights contributing more price discovery (Booth et al., 1999; Chu et al., 1999; Harris et al., 2002). More recently, Putniņš (2013) defined the information leadership share (ILS), which accounts for both the permanent component of CS and the variance measure of IS. Based on a series of simulations, Putniņš (2013) finds that only the ILS consistently identifies the first mover in the market.

Although the ILS was shown to improve upon both the CS and the IS, it still has shortcomings. The price discovery measure is restricted to bivariate markets, dependent on the ordering of the Cholesky decomposition, assumes one temporary and one permanent shock, and assumes uncorrelated reduced-form errors. Shen et al. (2024) addressed these shortcomings using their price discovery share (PDS), which estimates a market's contribution to the variance of efficient price innovations, analogous to the IS. The PDS is order-invariant, suitable for multivariate analysis, and insensitive to correlation. Similar to the ILS of Putniņš (2013), Shen et al. (2025) integrated the PDS variance-decomposition measure into their PILS measure.

Simultaneously, Lien et al. (2025) developed their own modern multivariate price discovery measure, the NLS, which used a structurally identified model to mitigate the shortcomings of previous studies. Their measure is also order-independent, amenable to multivariate analysis, and does not require the assumption of uncorrelated innovations. The NLS and PILS measures use structurally different identification strategies. Therefore, including both measures serves as a robustness check of the modern multivariate methods.

With the cash price combinations that meet the necessary criteria, including sufficient observations, nonstationary price series, and full rank cointegration, we estimate the VECM:

$$\Delta p_t = \alpha(\beta' p_{t-1} + c) + \sum_{j=1}^{J} \Gamma_j \Delta p_{t-j} + e_t. \tag{1}$$

In the VECM specification, p_t is a column vector of n prices in period t, α is a $n \times k$ matrix of error correction coefficients where k is the rank of cointegration, Γ_j is a $n \times n$ matrix of coefficients for the jth lag of first differences of prices that captures short-run dynamics, J is the maximum identified lag determined by BIC based selection for the market pair, and e_t is a vector of residuals for each price. In the cointegration relationships, β' is an $k \times n$ matrix of parameters for each price in each equation, and c is a $k \times 1$ vector of constants in the cointegrating relationship. With the parameters estimated from the VECM, we can calculate the NLS and PILS price discovery measures.

3.1.1 NLS

To estimate the NLS, α, β', and e are needed from the VECM regression (Lien et al., 2025). First, the decomposed permanent and transitory shocks are calculated as

$$\epsilon_t = \begin{pmatrix} \alpha_\perp \\ \beta' \end{pmatrix} e_t, \tag{2}$$

where $\alpha_\perp$ is the orthogonal complement of α following (Lien et al., 2025). When the prices are cointegrated rank $n-1$, $\alpha_\perp$ is an $1 \times n$ vector. Once ϵ_t is calculated, the covariance matrix is retrieved using $\Sigma = \sum_t \epsilon_t \epsilon_t'/T$, and the Cholesky decomposition of Σ is defined as LL', where L is the lower triangular Cholesky factor. Finally, matrix D_0 can be calculated using

$$D_0 = \begin{pmatrix} \alpha_\perp \\ \beta' \end{pmatrix}^{-1} L, \tag{3}$$

which contains the contemporaneous responses to permanent shocks in each market in the first row, labeled individually as $d^p_{0,i}$ for market i (Lien et al., 2025). Lien et al. (2025) shows that Equation 3 is not affected by the ordering of the price series, even though a Cholesky decomposition is required, maintaining the order-invariance of the NLS price discovery measures.

Using contemporaneous responses, we can estimate New Leadership and the NLS. First, for each market i, the New Leadership is calculated by dividing the contemporaneous response in i by the sum of contemporaneous responses in all other markets:

$$NL_i = \frac{d^p_{0,i}}{\sum_{l \neq i} d^p_{0,l}} \tag{4}$$

(Lien et al., 2025). To standardize the discovery measure, it is converted into a share of the total price discovery using

$$NLS_i = \frac{NL_i}{\sum_{l=1}^{n} NL_l}, \tag{5}$$

which leads to the total NLS of each market summing to one.

3.1.2 PILS

PILS is calculated by combining two previously established discovery measures: CS and PDS (Shen et al., 2025). First, to estimate the CS, we use

$$\Psi = \beta_{\perp}(\alpha'_{\perp}(I_n - \sum_{j=1}^{J} \Gamma_j)\beta_{\perp})^{-1}\alpha'_{\perp} \tag{6}$$

where $\beta_{\perp}$ represents the orthogonal complement of the cointegrating coefficient matrix (Shen et al., 2025). When each row vector of β' consists of a 1 and a -1, each row of Ψ is the same (Shen et al., 2025). We choose to follow common practice and estimate the VECM without restrictions on the cointegrating coefficients. Therefore, the estimated β' may take values not equal to 1 and -1, and the rows of Ψ may vary slightly. Across our estimated VECMs, the median relative deviation between rows is approximately 8 percent, and PILS estimates are consistent with the independently derived NLS measure of Lien et al. (2025), which requires no row-averaging, supporting the validity of this approximation in our application. We use the average for each column, with the average of the i^{th} column being defined as Ψ_i. Having redefined Ψ_i, the CS in market i can be calculated using

$$CS_i = \frac{\Psi_i}{\sum_{l=1}^{n} \Psi_l} \tag{7}$$

following Shen et al. (2025).

To estimate PDS, we again use the Ψ matrix from the CS and the error covariance matrix $\Omega = \sum_t e_t e'_t / T$. The equation for the price discovery share in market i is expressed as

$$PDS_i = \frac{\sum_{l=1}^{n} \Psi_i \times \Psi_l \times \sigma_{i,l}}{\Psi(1)\Omega\Psi(1)'}, \tag{8}$$

where $\Psi(1)$ is the $1 \times n$ row vector of column means, where element j equals $\frac{1}{k}\sum_{i=1}^{k} \Psi_{ij}$, summing over the k rows of Ψ. Parameter $\sigma_{i,l}$ is the covariance of i and l from Ω (Shen et al., 2025). Finally, the PDS and CS can be combined to estimate the price discovery for the information leadership measure of market i using

$$PIL_i = \frac{PDS_i}{CS_i}, \tag{9}$$

and the information leadership measures can be standardized into shares using the equation

$$PILS_i = \frac{PIL_i^2}{\sum_{l=1}^{n} PIL_l^2} \tag{10}$$

following Shen et al. (2025).

3.2 Calculating Changes in Price Discovery

Once price discovery measures are estimated, we can evaluate suitable market combinations in each time period and evaluate changes in price discovery over time. First, we determine the mean price discovery coming from crushing plants, river terminals, and, in the trivariate case, nearby futures. For market combinations that are cointegrated in multiple time periods, we compute the change in price discovery across the three markets over time.

Changes in price discovery were examined across four alternative sets of cointegrated markets to test the robustness of the results. First, we include all pairs of river terminals and soybean crushing plants that were cointegrated in at least one of three periods, regardless of market proximity. Second, we include all market pairs that remained cointegrated across all three time periods. Third, we include only the closest river terminal for each soybean crushing plant and the closest crushing plant for each river terminal with which it is cointegrated in at least one period. Fourth, we include only the proximity-based market pairs that were cointegrated in all three periods.

To determine whether the shift in the contribution of crushing plants, river terminals, and nearby futures to price discovery is statistically significant, we use the Welch two-sample t-test on period means and the one-sample Student's t-test on the mean change. We use the F-test to determine if the variances of two periods were statistically different. The Mann-Whitney U test and paired t-test were run for robustness, and the results are included in Appendix A for completeness.

4 Data

The length of the analyzed periods around the US-China Trade War was determined by using a structural break test. Starting with nearby futures prices for soybeans from September 15, 2014, to April 17, 2025, we identified that the optimal segmentation of the nearby futures had 4 breakpoints on April 18, 2016, June 12, 2018, December 14, 2020, and September 14, 2023, based on a BIC-based test for an unknown number of breakpoints. Each breakpoint date marks the first day of the subsequent period. Based on these four breaks, we identified the pre-trade-war period as April 18, 2016, to June 11, 2018; the trade-war period as June 12, 2018, to December 13, 2020; and the post-trade-war period as December 14, 2020, to September 13, 2023. The observations beyond the first and last breakpoints were removed. The changes and breaks in futures prices through the three maintained periods are shown in Figure 3. We use daily cash prices for soybean crushing plants and river terminals, along with nearby soybean futures, for each of the three periods in the analysis.

The internal breaks in the data align with the onset of the US-China trade war and its subsequent expansion. Our identified break on June 12, 2018, comes just before China announced retaliatory tariffs on soybeans on June 15, 2018. While US soybeans had not yet been targeted by trade policy, anticipation based on the ongoing trade conflict had already affected prices (Cowley, 2020). Our structural break closely echoes the findings of Adjemian et al. (2021) who identified June 26, 2018, as a break in the mean log difference between US and Brazil soybean prices.

While the Phase 1 Trade Agreement was signed in January 2020, soybean exports to China and nearby futures prices recovered during the fall of 2020 (DTN, 2025; USDA Foreign Agricultural Service, 2026). The December 14, 2020, break occurs midway through this recovery. Adjemian et al. (2021) also identifies a break in the mean log price difference in the fall of 2020, which is attributed to a resumption of regular seasonal fluctuations.

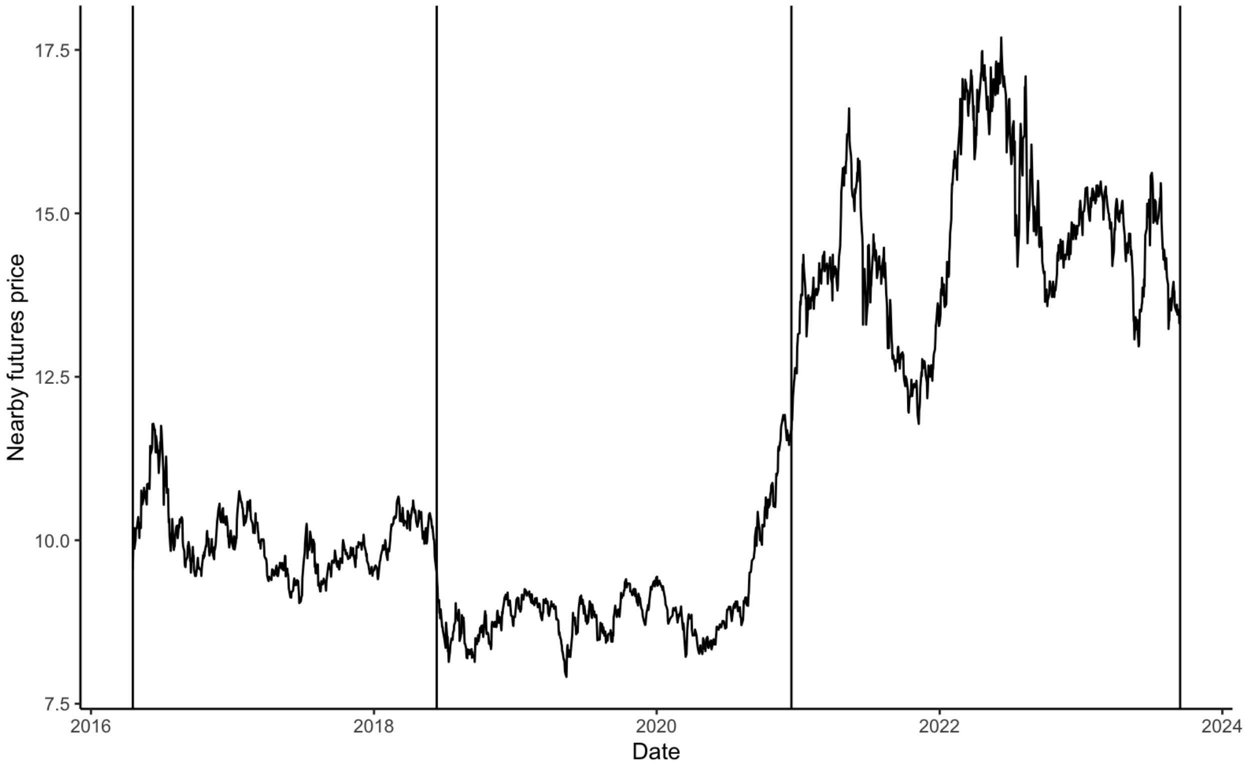

Figure 3: Nearby soybean futures prices ($/bu) from April 18, 2016, to September 13, 2023, delineated by BIC-identified structural breakpoints. Shaded regions correspond to the pre-trade-war (April 18, 2016–June 11, 2018), trade-war (June 12, 2018–December 13, 2020), and post-trade-war (December 14, 2020–September 13, 2023) periods. Data Source: DTN (2025)

Cash prices and futures data were collected from DTN's ProphetX application (DTN, 2025). Delivery points in Ohio, Indiana, Illinois, Minnesota, Iowa, and Missouri were selected based on high soybean production, the presence of soybean crushing plants, and proximity to the Mississippi and Ohio Rivers. There were 81 river terminals and 37 crushing plants across the six states. The price series for each of the 118 delivery points was split into three distinct time periods, with series excluded based on missing-observation thresholds and stationarity criteria. Table 1 shows the descriptive statistics of the price series for each period and the number of locations removed due to missing observations and stationarity.

There are multiple crushing plants and river terminals that were excluded across the three periods due to excessive missing observations. These were likely delivery points that were not yet open at the beginning of the period. On the other hand, very few of the cash price series across the three time periods were stationary. Specifically, none of the soybean crushing plant price series were stationary, and only five river terminal price series were stationary across the three periods. Stationary price series are excluded from the analysis since market cointegration requires I(1) price series.

Table 1: Summary statistics for daily cash prices at soybean crushing plants and river terminals, and nearby futures prices.

	Crush Plants	River Terminals	Nearby Futures
Pre-Trade War (Apr. 18, 2016 – Jun. 11, 2018)			
Locations dropped due to missing obs.	4	13	
Locations dropped due to stationarity	0	4	
Remaining Locations	33	64	
Observations	18,013	38,890	542
Mean ($/bu)	9.69	9.82	10.01
St. Dev. ($/bu)	0.55	0.57	0.51
Min ($/bu)	8.39	7.48	9.04
Max ($/bu)	19.35	19.37	11.78
Trade War (Jun. 12, 2018 – Dec. 13, 2020)			
Locations dropped due to missing obs.	3	9	
Locations dropped due to stationarity	0	0	
Remaining Locations	34	72	
Observations	21,522	47,068	633
Mean ($/bu)	8.74	8.84	9.03
St. Dev. ($/bu)	0.79	0.84	0.72
Min ($/bu)	7.14	6.94	7.91
Max ($/bu)	12.16	13.14	11.92
Post-Trade War (Dec. 14, 2020 – Sep. 13, 2023)			
Locations dropped due to missing obs.	3	4	
Locations dropped due to stationarity	0	1	
Remaining Locations	34	76	
Observations	24,056	54,393	691
Mean ($/bu)	14.50	14.56	14.57
St. Dev. ($/bu)	1.26	1.38	1.31
Min ($/bu)	11.16	11.29	11.70
Max ($/bu)	18.74	30.35	17.69

We expect crushing plants to maintain price premiums over other local buyers (Wu et al., 2025). However, in each period, the average cash price at river terminals was higher than at crushing plants, due to the spatial distribution of the included delivery points. When we observe crushing plant-river terminal pairs in proximity, the price at the crushing plant is found to be higher. Additionally, the gap between the two mean prices decreases throughout the three periods. The increasing price of crushing plants relative to river terminals aligns with river terminals becoming increasingly marginalized; however, further analysis of this finding is outside the scope of this research.

5 Results

The Johansen rank tests yielded 1,978, 1,367, and 1,951 cointegrated pairs of crushing plants and river terminals in the pre-trade-war, trade-war, and post-trade-war periods, respectively. The cointegrated pairs represent 94 percent, 56 percent, and 76 percent of the possible pairs across the three consecutive periods. The percentage of market pairs that were cointegrated decreased substantially between the pre-trade-war and trade-war periods, then partially recovered after the trade war. The robustness of our results to the four samples, including those based on persistent cointegration exclusion restrictions, is used to control for changes in the composition of cointegrated markets.

By construction, including nearby futures as a third price series in each cash price combination will result in fewer full rank cointegrated combinations. Non-cointegrated cash price pairs can't be cointegrated of rank-2 when futures are added. When futures prices were included, there were 664, 0, and 1,931 cointegrated market combinations of rank-2 between a crush plant, a river terminal, and nearby futures combinations before, during, and after the trade war periods, respectively. In the same trivariate Johansen rank tests, there were 1,297, 1,360, and 626 cointegrated exactly rank-1 combinations in the respective periods. Table 2 shows the number of cointegrated combinations of each rank in each period.

Given this break in cointegration involving nearby futures, we cannot estimate price discovery during the trade war in the multivariate setting. Therefore, the price discovery results are presented as follows. First, we discuss the breakdown in cointegration during the trade war. Second, we discuss the findings from bivariate cash market pairs comprising one river terminal and a soybean crushing plant across the pre-, post-, and trade war periods. Third, we discuss the findings from the pre- and post-trade war periods in the multivariate case, since cointegration is absent during the trade war.

The results indicate that the number of cointegration market pairs decreased during the trade war. However, when futures were included, there were no instances in which a single stochastic trend was present among a river terminal, a crushing plant, and nearby futures. Based on the bivariate results, we expect the 1 cointegration relationship in the trivariate case to be between the two cash prices. To confirm that the maintained relationship was in cash-price terms, we ran a pairwise Johansen test between each cash price and its nearby futures price during the trade-war period. We find that none of the local cash prices are cointegrated with the nearby futures price during the

Table 2: Number of cointegrated market combinations in each period determined by Johansen maximum eigenvalue statistics

	Pre-Trade War	Trade War	Post-Trade War
Panel A: Bivariate (crush plant–river terminal)			
Cointegrated pairs	1,978	1,367	1,951
Panel B: Trivariate (nearby futures–crush plant–river terminal)			
Not cointegrated (rank 0)	151	1,088	27
Cointegrated, rank-1	1,297	1,360	626
Cointegrated, rank-2	664	0	1,931
Panel C: Pairwise (cash location–nearby futures)			
Cointegrated cash locations	55	0	107

Note: Panel A reports the number of cash price pairs for which both price series are cointegrated rank-1, and the Johansen maximum eigenvalue statistics reject the null of no cointegration at the 5% level. Panel B tests each cash price pair augmented with the nearby futures price; the rank is the number of linearly independent cointegrating vectors identified by the Johansen maximum eigenvalue statistics. Panel C reports the number of cash locations individually cointegrated with the nearby futures price in a bivariate Johansen maximum eigenvalue test.

US-China trade war, whereas 55 and 107 cash prices are cointegrated with futures in the pre- and post-trade-war periods, respectively.

Our primary analysis examines data-driven pricing regimes influenced by the trade war. The designated beginning, June 12, 2018, aligns closely with the announcement and enactment of China's retaliatory tariffs. However, the designated end, December 13, 2020, is well after the Phase 1 Trade Agreement was signed in January 2020. The end date follows the return to normal monthly exports in August (USDA Foreign Agricultural Service, 2026), and returns to global pricing patterns (Adjemian et al., 2021). To assess the robustness of cointegration to periods designated by the start and end of the trade war, we rerun the Johansen tests with breaks on June 15, 2018, when China officially announced tariffs, and on January 15, 2020, the date of the signing of the Phase 1 Trade Agreement.

The results of the Johansen test with the trade war-based window are shown in Table 3. Under the alternative period assignment, there were only 15 trivariate combinations of cointegrated rank-2, well below the 713 and 1,873 before and after the trade war, respectively. Only 6 cash prices were cointegrated with nearby futures on a pairwise basis during the trade war. While the number of cointegrated relationships varies under policy-driven breaks, we still find that cointegration between cash and futures markets deteriorated during the US-China trade war. Following the trade war, markets became re-cointegrated at levels comparable to or exceeding those of the pre-trade-war period.

Further analysis of prices during the period provides qualitative insight regarding the broken long-run cointegrating relationship and the implications for future market shocks. Specifically, we eval-

Table 3: Number of cointegrated market combinations in each period determined by Johansen maximum eigenvalue statistics with trade war policy-driven breaks

	Pre-Trade War	Trade War	Post-Trade War
Panel A: Bivariate (crush plant–river terminal)			
Cointegrated pairs	2,029	758	1,891
Panel B: Trivariate (nearby futures–crush plant–river terminal)			
Not cointegrated (rank 0)	147	1,446	8
Cointegrated, rank 1	1,285	987	669
Cointegrated, rank 2	713	15	1,873
Panel C: Pairwise (cash location–nearby futures)			
Cointegrated cash locations	58	6	105

Note: Periods defined by trade war policies on June 15, 2018, and January 15, 2020. Panel A reports the number of cash price pairs for which both price series are cointegrated rank-1, and the Johansen maximum eigenvalue statistics reject the null of no cointegration at the 5% level. Panel B tests each cash price pair augmented with the nearby futures price; the rank is the number of linearly independent cointegrating vectors identified by the Johansen maximum eigenvalue statistics. Panel C reports the number of cash locations individually cointegrated with the nearby futures price in a bivariate Johansen maximum eigenvalue test.

uate changes in cash prices and the basis, a commonly used relationship between cash and futures prices. A delivery point's basis is calculated as the cash price minus the futures price. In our case, we use nearby futures. In addition, we evaluate changes in nearby soybean futures volume obtained from DTN ProphetX to determine whether daily trade volume differs across the three time periods (DTN, 2025). Table 4 shows the changes in the realized volatility of soybean prices and basis and the daily trade volume across our designated periods. Realized volatility is $\sqrt{\frac{1}{T}\sum_{t=1}^{T} r_t^2}$, where r_t is the daily return and T is the number of trading days in the period.

The trade war shifted soybean prices to lower levels, as shown in Figure 3. However, realized volatility in cash prices and the nearby basis decreased during the trade war. Specifically, the mean realized volatility of cash prices decreased by 42 percent, and that of the basis by 55 percent. Once cointegration returned following the trade war, we observed increased volatility in the basis. The pattern suggests that the high realized volatility in the basis reflects the cash and futures prices snapping back to the long-run equilibrium. However, the low realized volatility in basis during the period when cash prices were not cointegrated with nearby futures suggests that cash prices were steadily drifting apart. While the trade war disrupted price volatility, trade volume displayed a persistent trend across the three periods. The average daily trading volume decreased between both intervals, indicating reduced use of the soybean futures markets.

Table 4: Mean cash and basis realized volatility and nearby futures trading volume by period

	Pre-Trade War	Trade War	Post-Trade War
Mean Cash RV ($/bu)	0.168	0.098	0.218
Mean Basis RV ($/bu)	0.106	0.048	0.151
Mean Daily Volume (contracts)	80,167	71,757	65,808

Note: Realized volatility is computed as $\sqrt{\frac{1}{T}\sum_{t=1}^{T}(\Delta x_t)^2}$ where Δx_t is the daily change in the relevant price series and T is the number of trading days in the period. Values are averaged across all cash price locations passing the 85% observation coverage and ADF non-stationarity screens. Basis is defined as the cash price minus the nearby futures price. Trading volume is the mean daily volume of CME Group nearby soybean futures contracts accessed from DTN (2025).

5.1 Bivariate Cash Price Analysis

For the bivariate cash price pairs, VECMs were estimated for each market pair in the pre-trade-war, trade-war, and post-trade-war periods, as defined above. The number of lags ranged from 1 to 6 across the three periods. The highest maximum persistence occurred during the post-trade-war period, the only period that contains pairs with five or six lags. On average, the number of lags selected was consistent across the pre- and post-trade-war periods (1.22 and 1.20, respectively). The lowest persistence occurred during the trade war, in which only three pairs had three lags, and none exceeded three.

We also analyzed the number of lags selected using the Akaike Information Criterion (AIC) to determine if the relative lag lengths are consistent. Once again, the least persistence existed in the second period (2 lags). On average, the greatest persistence existed during the third period (3 lags), and the second greatest persistence was in the first period (2 lags). We include the results of the price discovery estimates using AIC in Table 12 of Appendix A for robustness.

Following the VECM estimation, we find that the residuals for each market-period combination have no unit root according to ADF tests. Using the results from the VECMs, the NLS and PILS price discovery measures were computed for each market pair in each period. Due to the large number of estimated regressions, the summary statistics for the period NLS and PILS of the crushing plant are presented in Table 5. The NLS and PILS of the river terminal are equal to 1 minus the respective discovery measure at the crushing plant. The NLS and PILS are reported together, since their calculations were identical in the pairwise comparison. Since NLS does not require the cointegrating vector to satisfy the $(1, -1)'$ restriction while PILS relies on the column-averaging approximation of Ψ described above, the agreement between the two measures mitigates concerns about sensitivity to the approximation.

The table is divided into four panels representing different cointegrated pairs. By construction, the number of cointegrated pairs in each sample decreases sequentially. Figure 4 shows the cointegrating relationships that were included in panels three and four, which were based on cointegrated pair proximity.

Table 5: Summary statistics for pre-trade war, trade war, and post-trade war price discovery measures at soybean crushing plants

	Pre-Trade War	Trade War		Post-Trade War	
	NLS_c & $PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$
Sample 1: All integrated market pairs					
Mean	0.48	0.47***	-0.00	0.40***	-0.07***
St. Dev.	0.07	0.07***	0.12	0.13***	0.18
Min	0.28	0.18	-0.35	0.00	-0.61
Max	0.76	0.72	0.33	0.73	0.36
Pairs	1,978	1,367	1,113	1,951	1,071
Sample 2: Pairs cointegrated in all three periods					
Mean	0.47	0.47	-0.00	0.39***	-0.08***
St. Dev.	0.07	0.08***	0.13	0.14***	0.16
Min	0.28	0.18	-0.35	0.00	-0.55
Max	0.76	0.72	0.33	0.71	0.33
Pairs	863	863	863	863	863
Sample 3: Geographically closest cointegrated pairs					
Mean	0.51	0.48***	-0.02*	0.44***	-0.03**
St. Dev.	0.08	0.07*	0.10	0.11***	0.14
Min	0.36	0.29	-0.24	0.00	-0.60
Max	0.73	0.68	0.27	0.67	0.28
Pairs	65	81	53	103	74
Sample 4: Geographically closest pairs cointegrated in all three periods					
Mean	0.51	0.49	-0.02	0.43***	-0.05***
St. Dev.	0.08	0.08	0.10	0.10*	0.11
Min	0.36	0.29	-0.24	0.00	-0.39
Max	0.73	0.68	0.27	0.67	0.28
Pairs	46	46	46	46	46

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Stars on NLS_c and $PILS_c$ in the Trade War and Post-Trade War columns indicate that the period mean is significantly different from the mean in the preceding period as determined by Welch's t-test. Stars on ΔNLS_c and $\Delta PILS_c$ indicate that the mean change is significantly different from zero as determined by Student's t-test. Stars on St. Dev. indicate that the variance is significantly different from the variance in the preceding period based on an F-test. Because $NLS_c = PILS_c$ in the bivariate case, each cell reports a single value. All reported discovery measures are for the crushing plant; river terminal discovery equals one minus the crushing plant value.

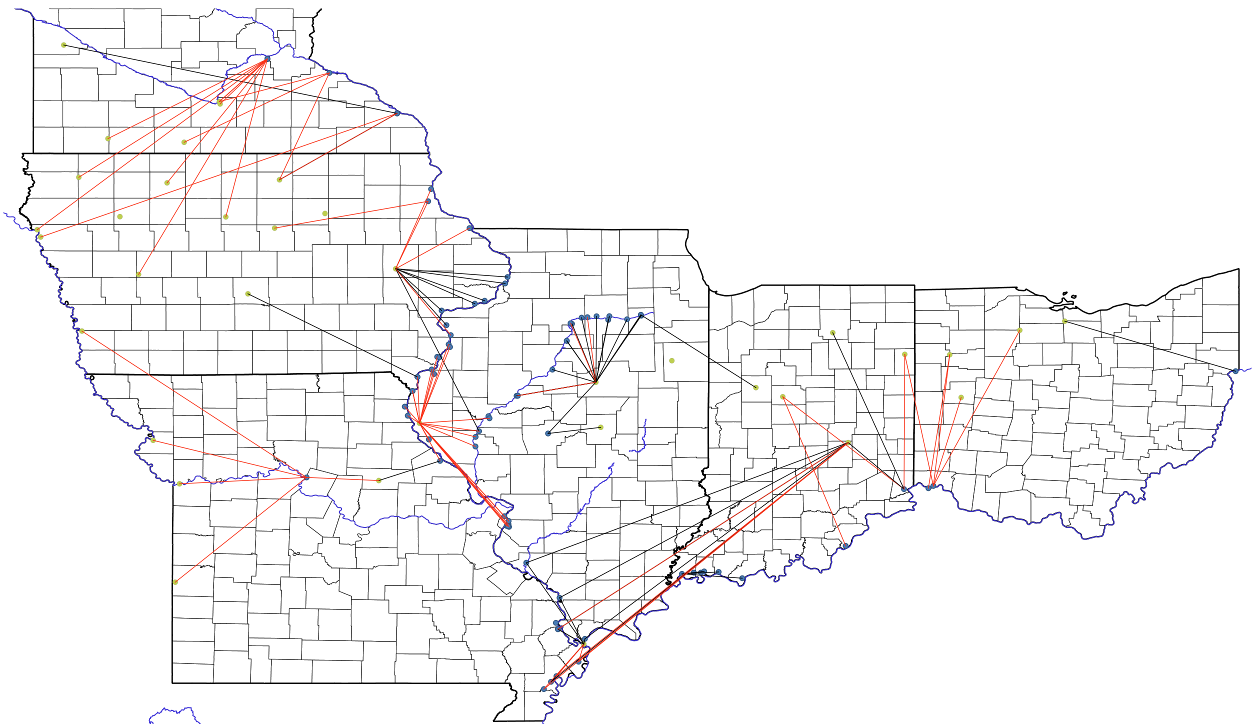

Figure 4: Map of closest cointegrated relationships between river terminals and soybean crushing plants as denoted by connecting lines. Blue dots mark river terminals, and green dots mark soybean crushing plants. Black lines indicate the two locations were cointegrated during all three periods. Red lines indicate locations where cointegration occurred in at least one period but not in all three.

Across all four samples, the mean soybean crushing plant price discovery decreased over time. Between the pre-trade-war and trade-war periods, shifts in mean price discovery from crush plants ranged from 0 to 3 percentage points. However, the means differed statistically only at the 0.01 significance level in the first sample (a 1-percentage-point decrease) and the third sample (a 3-percentage-point decrease). Larger changes in mean price discovery at soybean crushing plants were observed between the trade-war and post-trade-war periods. In the two proximity-based samples, mean price discovery was 4–6 percentage points lower after the trade war. In the broader samples, the mean price discovery measure was 7–8 percentage points lower after the trade war. All four sample means differed between the two periods at the 0.01 significance level.

To visualize the price discovery of crushing plants over time, Figure 5 depicts the distribution of price discovery across the four samples. The distribution in the post-trade war period is noticeably shifted to the left relative to the other two distributions. Additionally, we observe greater variability and left-skewness in the price discovery of crushing plants during the trade war and post-trade war periods. The observed 0.00 price discovery measures in the third period are largely attributable to the Louis Dreyfus soybean crushing plant in Claypool, Indiana[5]. These patterns pull down the NLS and PILS price discovery measures for crush plants in the post-trade-war period.

Given the varying numbers of cointegrated pairs across time periods and columns of Table 5, the t-tests on mean price discovery discussed above are based on an unbalanced sample. On the other hand, the Δ columns show how soybean crushing plants' price discovery has changed within cash price pairs that are cointegrated in two consecutive periods. The average change in price discovery is within 1 percentage point of the change in average price discovery measure, but the Δ column suggests slightly smaller decreases in crush price discovery. Between the pre- and trade war periods, the mean Δ in crush plant price discovery was between 0 and 2 percentage points across the four samples. However, none of the mean Δs were statistically different from zero during the first interval. The price discovery Δ between the trade war and post-trade war periods was more pronounced. Specifically, the mean change in the crush plant price discovery was 3 to 8 percentage points. Once again, the largest decreases occurred in the larger sample, which includes more than just the closest cointegrated markets. All four mean Δs were statistically different from zero at the 0.05 significance level. Additionally, the difference between the change in the mean and the mean change across periods was within 1 percentage point, indicating that the results are not sensitive to balanced versus unbalanced samples.

Figure 6 shows the distribution of changes in price discovery across the two intervals in all four samples. The distribution between the pre-trade-war and trade-war periods appears centered at zero, with a similar number of soybean crushing plants experiencing increases and decreases in price discovery within cash price pairs. However, across all trade-war-to-post-trade-war intervals, we observe distributions centered to the left of zero.

Additionally, the change in the latter period shows greater left-skewness, with more cointegrated cash price pairs exhibiting decreasing soybean crushing plants price discovery. In the two broader samples, we observe bimodal distributions, with a secondary peak centered on a 40-percentage-

[5] see robustness results in Appendix A

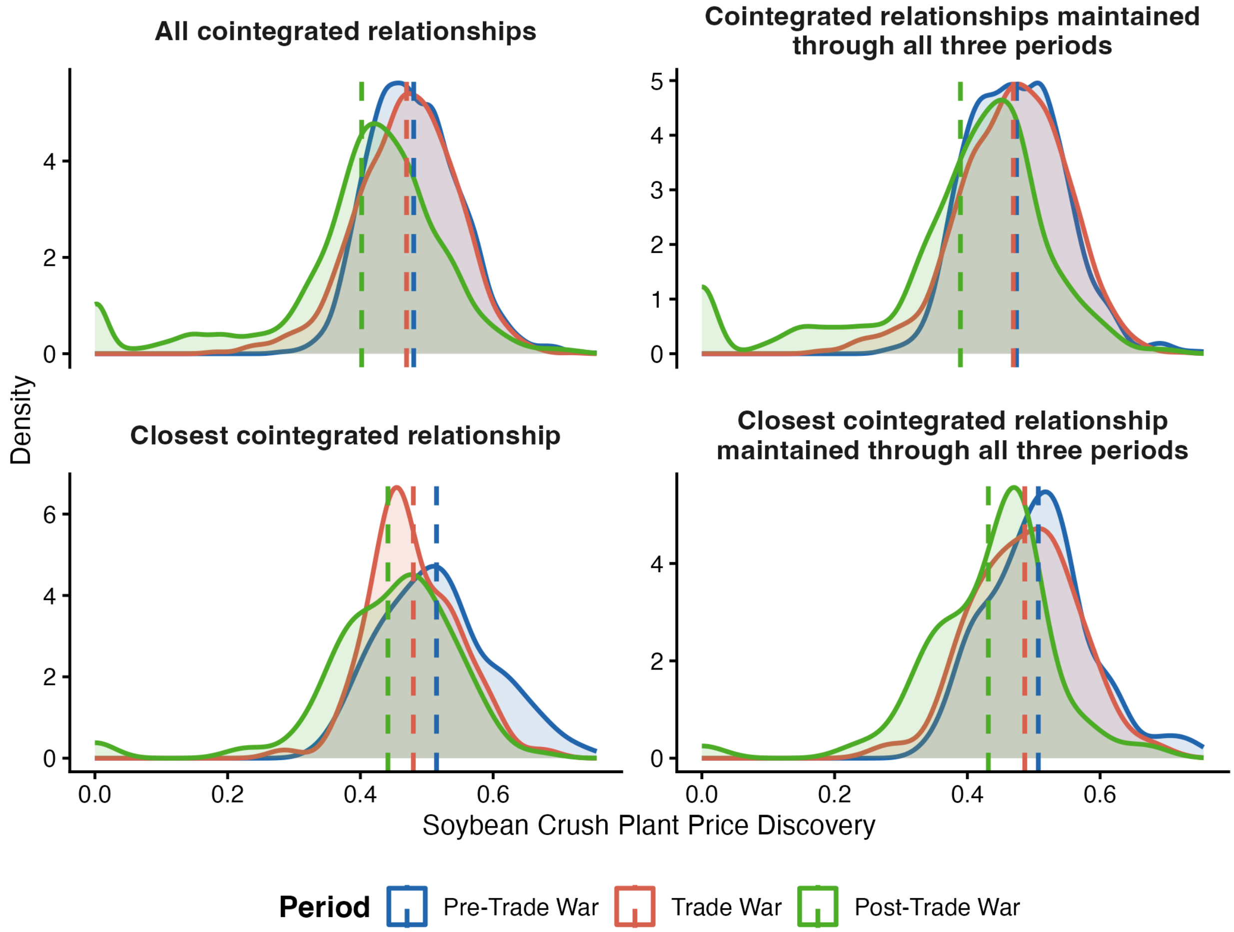

Figure 5: Kernel density plot of soybean crushing plants' price discovery across the three time periods for all market pairs. Vertical dashed lines of the respective colors represent the sample means.

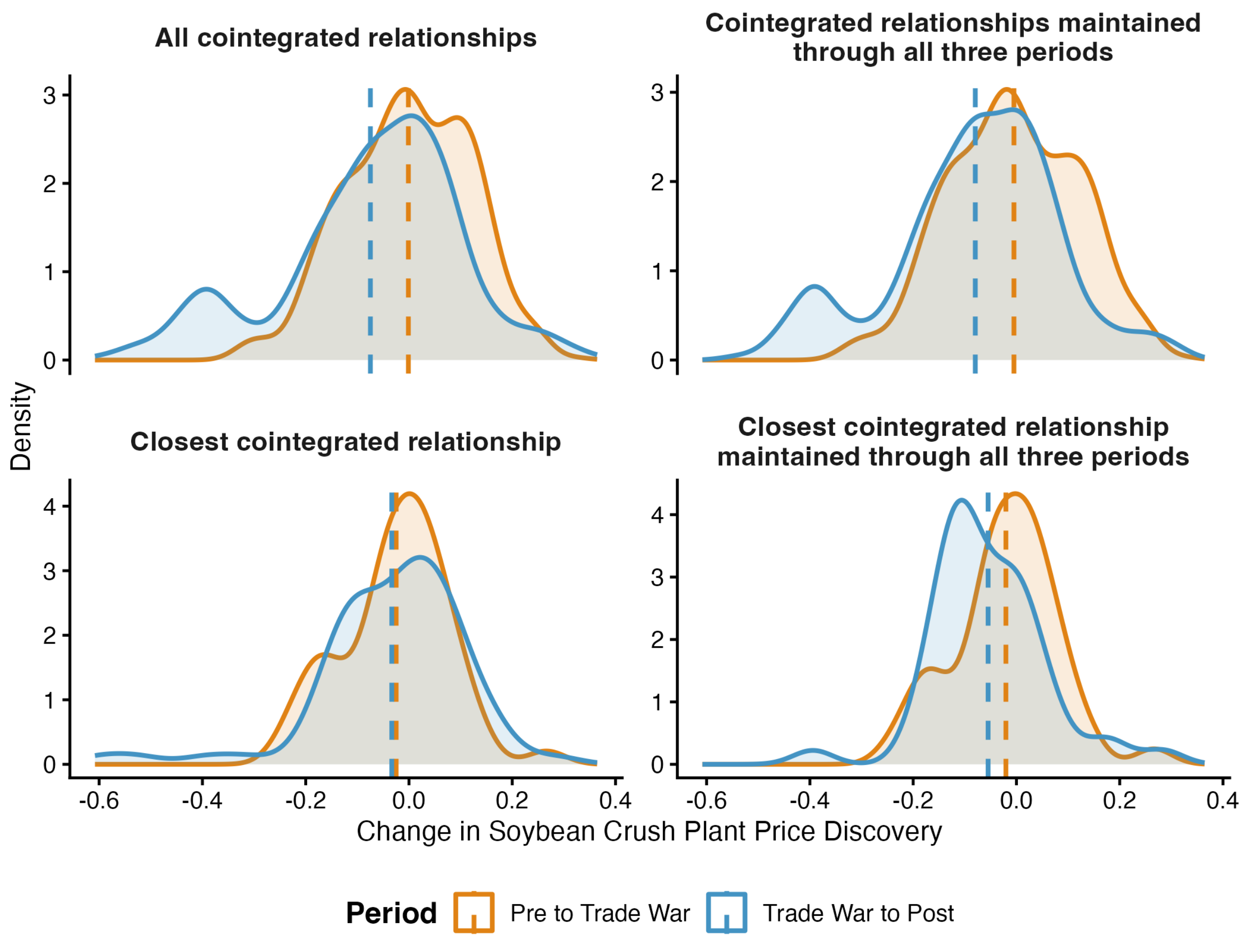

Figure 6: Kernel density plots of change in soybean crushing plants' price discovery across the two intervals. Vertical dashed lines of the respective colors represent the sample means. Only market pairs that were cointegrated in both periods of a respective interval are included.

point decrease in price discovery from soybean crushing plants. This secondary peak is primarily attributable to market pairs that include the Louis Dreyfus crush plant in Claypool, Indiana; the Cargill crush plant in Iowa Falls, Iowa; or the Consolidated Grain and Barge river terminal in Portageville, Missouri.

The results of the bivariate analysis without the three outliers are shown in Table 7 in Appendix A. Excluding the three locations that produce extreme post-period price discovery values leaves the pre-trade-war and trade-war means unchanged across all four samples. Post-trade-war sample means increase by 2–4 percentage points across the four samples. However, changes in statistical significance occurred only in the third sample. The differences in the period means were not statistically different from zero, and the mean change between the trade-war and post-trade-war periods was statistically significant only at the 0.10 level after excluding the outliers.

In addition to evaluating the means, we observe that the variance of price discovery is relatively stable in the first two periods and greatest in the third period. The standard deviation of price discovery estimates across the first two periods was at most 1 percentage point. We still observe that the sequential variances differed at the 0.01 significance level in the first, second, and third samples. Between the trade-war and post-trade-war periods, standard deviations increased by 2–6 percentage points. However, when the three outliers listed above were excluded, the largest change in standard deviation was 2 percentage points. While statistical significance remains in samples 1 and 2, the magnitude of change in the standard deviations is less than a third without the outliers.

Broadly, the findings were robust to both unbalanced and balanced cointegrated-pair samples, as evidenced by changes in means and mean changes across periods in the four panels of Table 5. Additionally, the statistical significances of the period means were largely robust to the Mann-Whitney U test and, when appropriate, the paired t-test. The mean changes in price discovery were largely robust to the Wilcoxon signed-rank test. The only loss of significance occurs in the third sample when running the alternative tests. The statistical significances from the alternative tests are shown in Table 8 of Appendix A. Finally, we find that the results were robust to alternative missing-observation cutoffs of 10 and 20 percent, cubic spline interpolation, and AIC-based lag selection as shown in Tables 9–12 of Appendix A.

5.2 Multivariate Cash Price and Nearby Futures Analysis

For the multivariate cash-price and nearby-futures combinations, we followed a similar procedure to estimate VECM in each period as in the bivariate analysis. However, because there were no combinations with two cointegrating relationships during the trade war, we can estimate price discovery parameters only for market combinations in the pre- and post-trade-war periods. The number of lags selected by BIC ranged from 1 to 4 across the two periods, indicating less persistence in the market combinations than in the bivariate case. On average, the number of lags selected in each of the two time periods was 1. Although we rely on BIC-based lag selection, the AIC-recommended number of lags followed a similar pattern to the bivariate case, with 1 more lag recommended in the third period than in the first.

As in the bivariate case, residuals were confirmed to have no unit root by ADF tests. Using the VECM coefficients and residuals, the NLS and PILS price discovery measures were calculated. Summary statistics of price discovery measures for crush plants and river terminals for the multivariate models are shown in Table 6. The structure of the four samples in the multivariate case is identical to that in the bivariate case. Nearby futures price discovery and changes in price discovery can be calculated as the remaining share of price discovery. Similarly, the mean change in nearby futures price discovery is calculated such that the aggregated change in price discovery is zero. While we focus on changes in price discovery from cash-price markets, the summary statistics for the futures price discovery measures are presented in Table 13 in Appendix A, which also report statistical significance.

Before the trade war, nearby futures contributed 34 to 36 percent, crush plants contributed 32 to 36 percent, and river terminals contributed 29 to 32 percent of price discovery on average across the local markets in the four samples. After the trade war, the mean price discovery from river terminals increased to 37 to 41 percent, the nearby futures price discovery decreased to 32 to 33 percent, and the crush plant price discovery decreased to 27 to 31 percent. These ranges reflect variation across the four samples. Within any individual market combination, the shares sum to 100 percent. The trends in cash markets' price discovery are consistent with those in the bivariate analysis. While crushing plants and nearby futures led price discovery in the average market before the trade war, river terminals took over the largest share of price discovery after the trade war.

The NLS and PILS price discovery measures yield consistent results, with their means differing by at most 2 percentage points. Across the sample of estimated price discoveries in the trivariate combinations, the greatest difference between NLS and PILS estimates was 6.5 percentage points, and the mean was 1.1 percentage points. Between the pre- and post-trade-war periods, the predominant price-discovery market shifted.

The directional change for the two types of buyers was the same in both the bivariate and trivariate cases. Another consistent trend across the bivariate and trivariate results is an increase in price-discovery variances across all markets during the post-trade-war period. However, variance is consistently lower in the multivariate price discovery estimation than in the bivariate analysis. The lower variance may suggest that the inclusion of nearby futures provides a more stable estimation of price discovery across the included market combinations.

When examining the mean Δ in price discovery, the unbalanced and balanced samples yield consistent results because the multivariate analysis spans only two periods. Every market combination contributing to the Δ must be cointegrated in both periods. While the Δ calculation only compares the pre- and post-trade war periods, we still find that the mean Δ in price discovery from river terminals increases. The mean change ranges from 7 to 9 percentage points. Additionally, the mean Δ in crush plant price discovery decreased by five to six percentage points. Both results are consistent with the directional finding from the bivariate analysis. Consistent with the bivariate analysis, the change in average price discovery and the average change in price discovery were within 1 percentage point of each other, suggesting robustness across the unbalanced and balanced samples. In all four samples across both price discovery measures, the unbalanced mean price discovery measures in the two periods and the balanced mean Δ are statistically different from zero

Table 6: Summary statistics for pre-trade war and post-trade war price leadership measures at soybean crushing plants and river terminals

	Pre-Trade War				Post-Trade War				Δ			
	NLS_c	$PILS_c$	NLS_r	$PILS_r$	NLS_c	$PILS_c$	NLS_r	$PILS_r$	NLS_c	$PILS_c$	NLS_r	$PILS_r$
Sample 1: All integrated market pairs												
Mean	0.32	0.32	0.32	0.32	0.28***	0.27***	0.39***	0.40***	-0.05***	-0.06***	0.07***	0.09***
St. Dev.	0.03	0.04	0.03	0.04	0.08***	0.09***	0.08***	0.09***	0.09	0.10	0.07	0.09
Min	0.22	0.19	0.19	0.15	0.00	0.00	0.20	0.16	-0.38	-0.40	-0.10	-0.13
Max	0.45	0.49	0.41	0.43	0.44	0.48	0.99	1.00	0.14	0.18	0.47	0.54
Pairs	663	663	663	663	1,885	1,885	1,885	1,885	474	474	474	474
Sample 2: Pairs cointegrated in both periods												
Mean	0.32	0.32	0.32	0.31	0.28***	0.26***	0.39***	0.41***	-0.05***	-0.06***	0.07***	0.09***
St. Dev.	0.03	0.05	0.03	0.04	0.08***	0.09***	0.06***	0.07***	0.09	0.10	0.07	0.09
Min	0.22	0.19	0.19	0.15	0.00	0.00	0.28	0.26	-0.38	-0.40	-0.10	-0.13
Max	0.45	0.49	0.41	0.43	0.42	0.44	0.80	0.86	0.14	0.18	0.47	0.54
Pairs	474	474	474	474	474	474	474	474	474	474	474	474
Sample 3: Geographically closest cointegrated pairs												
Mean	0.35	0.35	0.31	0.30	0.31***	0.30***	0.37***	0.38***	-0.05**	-0.05**	0.07***	0.08***
St. Dev.	0.04	0.05	0.04	0.05	0.07***	0.08**	0.08***	0.09***	0.09	0.10	0.07	0.08
Min	0.28	0.26	0.20	0.16	0.00	0.00	0.23	0.20	-0.35	-0.36	-0.01	-0.01
Max	0.42	0.45	0.39	0.40	0.39	0.41	0.96	0.96	0.07	0.09	0.27	0.28
Pairs	23	23	23	23	104	104	104	104	18	18	18	18
Sample 4: Geographically closest pairs cointegrated in both periods												
Mean	0.35	0.36	0.30	0.29	0.31**	0.31**	0.37***	0.37***	-0.05**	-0.05**	0.07***	0.08***
St. Dev.	0.04	0.05	0.04	0.05	0.08***	0.08**	0.06	0.06	0.09	0.10	0.07	0.08
Min	0.28	0.26	0.20	0.16	0.00	0.00	0.32	0.32	-0.35	-0.36	-0.01	-0.01
Max	0.42	0.45	0.39	0.40	0.38	0.40	0.57	0.57	0.07	0.09	0.27	0.28
Pairs	18	18	18	18	18	18	18	18	18	18	18	18

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Stars on Mean in the Post-Trade War columns indicate the mean is significantly different from the corresponding Pre-Trade War mean as determined by Welch's t-test. Stars on Mean in the Δ columns indicate the mean change is significantly different from zero as determined by Student's t-test. Stars on St. Dev. in the Post-Trade War columns indicate that the variance is significantly different from the Pre-Trade War variance based on an F-test. Subscript c denotes price discovery measures at crush plants, and subscript r denotes price discovery measures at river terminals.

at the 0.05 significance level based on t-tests.

6 Discussion

We find that price discovery is not static and that shifts in price discovery align with price regimes characterized by changes in soybean demand. Additionally, global market volatility can remove the cointegration between cash and futures markets. Finally, even when futures markets are cointegrated with nearby futures, the futures' contribution to price discovery has decreased. The results have several implications.

First, we find that soybean cash markets break cointegration with the nearby futures during the US-China trade war. The finding is largely robust across alternative definitions of the trade war period, including both data-driven and policy-based break dates. The relationship between soybean cash prices and futures prices has been thoroughly investigated. Arnade and Hoffman (2015) estimate VECMs over three time periods from 1992 to 2013, suggesting that the prices are cointegrated. Similarly, Dimpfl et al. (2017) find cointegrated futures and spot prices between 1992 and 2014. In international markets, Samak et al. (2020) show that soybean spot prices from the World Bank International Commodity Prices were cointegrated with Chicago Board of Trade futures between 2010 and 2018, and Chen et al. (2023) shows that Chinese spot soybean prices were cointegrated with futures for the period 2009 to 2020. As far as we are aware, this is the first study to identify a temporary loss of cointegration between soybean futures and cash prices[6].

Soybean producers and buyers regularly use futures markets to mitigate risk through various hedging strategies. Cointegrated futures and cash prices imply a stable long-run relationship and mean-reverting basis, which supports effective hedging. A loss in cointegration broke this stability. The loss of cointegration in market pairs during the trade war period reflects a fundamental disruption in price transmission between futures and cash markets. The return to cointegration in the post-trade-war period suggests that the long-run cointegrating relationship was restored.

Second, while all cash prices became decoupled from nearby futures, many river terminals and crushing plants remained cointegrated with one another throughout the three periods. The maintained relationships are expected, particularly given the proximity of several delivery points that would be expected to compete for farmers' soybeans. Across the three time periods, there is a clear shift in price discovery from soybean crushing plants to river terminals. However, the largest shift does not occur during the trade war but rather after markets recover from it. The transition is consistent across four market-pair samples and statistically significant. While there is a shift in the dominant price discovery market, both the river terminals and the crushing plant continue to contribute to local markets. This multi-market contribution is consistent with the simultaneous causality found by Lewis et al. (2012).

[6]Unlike the temporary cointegration loss identified here, Xu (2018) finds permanent non-cointegration between corn cash prices and futures prices as a function of distance.

The timing of the effect suggests that the change may be driven by increased demand for crushed soybeans rather than by the brief trade disruption. Because crush plants have a consistent demand for soybeans and often maintain a price premium, they may be less responsive to price signals and market information. On the other hand, river terminals have more variable demand driven by global factors, and may be more responsive to market signals. Persistent demand from soybean crushing plants and variable, globally driven demand at river terminals leads to an increased share of price discovery for river terminals.

Third, while we cannot estimate the contribution of futures to price discovery during the trade war, we can evaluate changes between the pre- and post-trade-war periods. We find that price discovery from nearby futures markets has declined over time, indicating that cash prices in local markets increasingly drive underlying soybean prices. During the same interval, we see an 18 percent decrease in daily trade volume from the first to the third period. Hu et al. (2020) show that price discovery between different futures contracts rolls to deferred months as trading volume moves. It is possible that we observe similar declines in futures contributions to cash markets as traders reduce their use of nearby futures contracts for soybeans.

7 Conclusion

Over 90 percent of US soybean production is destined for domestic crushing or export (USDA ERS, 2026). However, trade policy in recent years has made annual exports more volatile, as domestic crushing has expanded in response to demand from the renewable diesel boom. The 2018–2020 US-China Trade War delineates three price regimes that we analyze: pre-war, trade-war, and post-trade-war. We examine how local price discovery between river terminals and crush plants evolved during the three unique price regimes.

The findings of this study are threefold. First, we find that price discovery shifted from the crush plants to river terminals in local cash markets. The shift largely occurred between the trade war and the post-trade war periods. Second, when nearby futures were included in the analysis, we find that no cash prices were cointegrated with nearby futures during the trade war. Third, between the pre-trade-war and post-trade-war periods, we find that price discovery from nearby futures decreases. Robustness tests using alternative market samples, missing-data thresholds, interpolation methods, period definitions, and lag selection criteria confirm the stability of our main findings.

While we find that our results are robust across several specifications, we recognize that there are still limitations to the work. First, the research design focuses on local markets defined by pairwise comparisons in six states, where numerous crushing plants and river access are available. These results may not be representative of states in the Pacific Northwest, where rail is more commonly used to move grains for export. Second, we rely on daily cash price series rather than the high-frequency price data. Daily cash prices may not capture within-day price adjustment dynamics. Therefore, intraday data might reveal cointegrating relationships not visible at daily frequency.

We believe that our results yield multiple market implications. Although soybean crushing plants have contributed an increasing share of US demand, local river terminals representing export demand have been faster to integrate new information into prices as volatility in global trade has increased. Crushing plants' persistent demand for soybeans in local markets exceeds that of river terminals. The results suggest that they are slower to respond to new information and instead follow local prices.

In controlling for price discovery from futures markets, we find that cash prices were not cointegrated with nearby futures during the 2018–2020 US-China Trade War. Therefore, the long-run equilibrium between cash and futures prices was broken during the global market disruption. Soybean producers and buyers both rely on futures markets to employ risk-mitigating strategies. A breakdown in the relationship between cash prices and futures prices may increase volatility in hedging outcomes, directly undermining the purpose of hedging.

The findings and limitations of this research provide opportunities for further exploration. First, the analysis can be expanded further South to include additional delivery locations near the Gulf, which are closer to the export site. Expanding the region may also enable analysis of how local price discovery varies across regions with different local demand drivers. Second, while the NLS and PILS allow estimation of price discovery in multivariate models, the required VECMs still limit the scale of analysis. Employing recent developments in high-dimensional time-series methods may enable a more comprehensive evaluation of additional local market relationships and the integration of more buyers. Third, the loss of futures and cash cointegration and the effects of shocks on the effectiveness of marketing strategies warrant exploration. The combination of cointegration breaking and low realized volatility suggests that the cash prices steadily diverged from futures during the trade war. While we hypothesize that the loss of a long-run equilibrium between cash and futures can increase hedging volatility, further research on the outcomes of alternative hedging strategies during market disruption is warranted. Fourth, a decrease in price discovery contribution from nearby futures coincided with a decrease in daily futures trading volume. While this aligns with the finding of Hu et al. (2020) that price discovery in futures markets rolls to deferred contracts as expiration approaches, we conduct no formal analysis and leave this to future research.

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A Appendix

Table 7: Summary statistics for pre-trade war, trade war, and post-trade war price discovery measures at soybean crushing plants, excluding Louis Dreyfus Commodities (Claypool, IN), CGB Linda Landing (Portageville, MO), and Cargill (Iowa Falls, IA)

	Pre-Trade War	Trade War		Post-Trade War	
	NLS_c & $PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$
Sample 1: All integrated market pairs					
Mean	0.48	0.47***	-0.00	0.43***	-0.02***
St. Dev.	0.07	0.07***	0.12	0.08***	0.12
Min	0.28	0.18	-0.35	0.14	-0.39
Max	0.76	0.72	0.33	0.73	0.36
Pairs	1,852	1,221	1,012	1,775	930
Sample 2: Pairs cointegrated in all three periods					
Mean	0.48	0.47	-0.01	0.43***	-0.04***
St. Dev.	0.07	0.08**	0.12	0.08**	0.12
Min	0.28	0.18	-0.35	0.14	-0.39
Max	0.76	0.72	0.33	0.71	0.33
Pairs	764	764	764	764	764
Sample 3: Geographically closest cointegrated pairs					
Mean	0.51	0.48***	-0.02	0.46*	-0.01
St. Dev.	0.08	0.06**	0.10	0.08	0.10
Min	0.36	0.29	-0.24	0.24	-0.20
Max	0.73	0.68	0.27	0.67	0.28
Pairs	64	77	52	99	70
Sample 4: Geographically closest pairs cointegrated in all three periods					
Mean	0.51	0.49	-0.02	0.44***	-0.05***
St. Dev.	0.08	0.08	0.10	0.08	0.10
Min	0.36	0.29	-0.24	0.24	-0.20
Max	0.73	0.68	0.27	0.67	0.28
Pairs	45	45	45	45	45

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Stars on NLS_c and $PILS_c$ in the Trade War and Post-Trade War columns indicate that the period mean is significantly different from the mean in the preceding period as determined by Welch's t-test. Stars on ΔNLS_c and $\Delta PILS_c$ indicate that the mean change is significantly different from zero as determined by Student's t-test. Stars on St. Dev. indicate that the variance is significantly different from the variance in the preceding period based on an F-test. Because $NLS_c = PILS_c$ in the bivariate case, each cell reports a single value. All reported discovery measures are for the crushing plant; river terminal discovery equals one minus the crushing plant value.

Table 8: Mann–Whitney U-test and paired t-test results for bivariate price discovery at soybean crushing plants

	Pre-Trade War	Trade War		Post-Trade War	
	NLS_c & $PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$
Sample 1: All integrated market pairs					
Mean	0.48	0.47†††	-0.00	0.40†††	-0.07†††
Pairs	1,978	1,367	1,113	1,951	1,071
Sample 2: Pairs cointegrated in all three periods					
Mean	0.47	0.47	-0.00	0.39***†††	-0.08†††
Pairs	863	863	863	863	863
Sample 3: Geographically closest cointegrated pairs					
Mean	0.51	0.48††	-0.02	0.44††	-0.03
Pairs	65	81	53	103	74
Sample 4: Geographically closest pairs cointegrated in all three periods					
Mean	0.51	0.49	-0.02	0.43***†††	-0.05†††
Pairs	46	46	46	46	46

Note: *, **, and *** denote 10%, 5%, and 1% significance from a paired t-test; reported only for Samples 2 and 4 whose balanced panels permit a valid paired comparison. †, ††, and ††† denote the same significance levels from a Mann–Whitney U-test comparing each period mean to the preceding period mean (period mean columns) or a Wilcoxon signed-rank test of the null that the mean change equals zero (Δ columns); reported for all samples. Because $NLS_c = PILS_c$ in the bivariate case, each cell reports a single value. River terminal discovery equals one minus the crushing plant value.

Table 9: Pre-trade war, trade war, and post-trade war price discovery at soybean crushing plants (robustness: 10% missing observation cutoff)

	Pre-Trade War	Trade War		Post-Trade War	
	NLS_c & $PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$
Sample 1: All integrated market pairs					
Mean	0.48	0.47***	-0.00	0.40***	-0.07***
St. Dev.	0.07	0.07***	0.12	0.13***	0.16
Min	0.28	0.18	-0.35	0.00	-0.55
Max	0.76	0.72	0.33	0.73	0.36
Pairs	1,978	1,335	1,113	1,885	1,019
Sample 2: Pairs cointegrated in all three periods					
Mean	0.47	0.47	-0.00	0.39***	-0.08***
St. Dev.	0.07	0.08***	0.12	0.14***	0.16
Min	0.28	0.18	-0.35	0.00	-0.55
Max	0.76	0.72	0.33	0.68	0.32
Pairs	848	848	848	848	848
Sample 3: Geographically closest cointegrated pairs					
Mean	0.51	0.48***	-0.02*	0.44***	-0.03*
St. Dev.	0.08	0.06**	0.10	0.11***	0.11
Min	0.36	0.29	-0.24	0.00	-0.39
Max	0.73	0.68	0.27	0.60	0.19
Pairs	66	80	53	98	70
Sample 4: Geographically closest pairs cointegrated in all three periods					
Mean	0.51	0.49	-0.02	0.42***	-0.07***
St. Dev.	0.08	0.08	0.10	0.10	0.10
Min	0.36	0.29	-0.24	0.00	-0.39
Max	0.73	0.68	0.27	0.59	0.19
Pairs	44	44	44	44	44

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Stars on NLS_c and $PILS_c$ in the Trade War and Post-Trade War columns indicate that the period mean is significantly different from the mean in the preceding period as determined by Welch's t-test. Stars on ΔNLS_c and $\Delta PILS_c$ indicate that the mean change is significantly different from zero as determined by Student's t-test. Stars on St. Dev. indicate that the variance is significantly different from the variance in the preceding period based on an F-test. Because $NLS_c = PILS_c$ in the bivariate case, each cell reports a single value. River terminal discovery equals one minus the crushing plant value.

Table 10: Pre-trade war, trade war, and post-trade war price discovery measures at soybean crushing plants (robustness: 20% missing observation cutoff)

	Pre-Trade War	Trade War		Post-Trade War	
	NLS_c & $PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$
Sample 1: All integrated market pairs					
Mean	0.48	0.47***	-0.00	0.40***	-0.07***
St. Dev.	0.07	0.07***	0.12	0.13***	0.18
Min	0.28	0.18	-0.35	0.00	-0.61
Max	0.76	0.72	0.33	0.73	0.36
Pairs	1,978	1,367	1,113	1,951	1,071
Sample 2: Pairs cointegrated in all three periods					
Mean	0.47	0.47	-0.00	0.39***	-0.08***
St. Dev.	0.07	0.08***	0.13	0.14***	0.16
Min	0.28	0.18	-0.35	0.00	-0.55
Max	0.76	0.72	0.33	0.71	0.33
Pairs	863	863	863	863	863
Sample 3: Geographically closest cointegrated pairs					
Mean	0.51	0.48***	-0.02*	0.44***	-0.03**
St. Dev.	0.08	0.07*	0.10	0.11***	0.14
Min	0.36	0.29	-0.24	0.00	-0.60
Max	0.73	0.68	0.27	0.67	0.28
Pairs	65	81	53	103	74
Sample 4: Geographically closest pairs cointegrated in all three periods					
Mean	0.51	0.49	-0.02	0.43***	-0.05***
St. Dev.	0.08	0.08	0.10	0.10*	0.11
Min	0.36	0.29	-0.24	0.00	-0.39
Max	0.73	0.68	0.27	0.67	0.28
Pairs	46	46	46	46	46

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Stars on NLS_c and $PILS_c$ in the Trade War and Post-Trade War columns indicate that the period mean is significantly different from the mean in the preceding period as determined by Welch's t-test. Stars on ΔNLS_c and $\Delta PILS_c$ indicate that the mean change is significantly different from zero as determined by Student's t-test. Stars on St. Dev. indicate that the variance is significantly different from the variance in the preceding period based on an F-test. Because $NLS_c = PILS_c$ in the bivariate case, each cell reports a single value. River terminal discovery equals one minus the crushing plant value.

Table 11: Pre-trade war, trade war, and post-trade war price discovery measures at soybean crushing plants (robustness: cubic spline interpolation)

	Pre-Trade War	Trade War		Post-Trade War	
	NLS_c & $PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$
Sample 1: All integrated market pairs					
Mean	0.47	0.47	-0.00	0.41***	-0.05***
St. Dev.	0.09	0.07***	0.12	0.11***	0.15
Min	0.00	0.25	-0.34	0.00	-0.60
Max	0.87	0.68	0.46	1.00	0.53
Pairs	1,661	1,295	933	1,654	902
Sample 2: Pairs cointegrated in all three periods					
Mean	0.46	0.47	0.01	0.41***	-0.05***
St. Dev.	0.09	0.07***	0.12	0.10***	0.14
Min	0.00	0.25	-0.34	0.00	-0.54
Max	0.80	0.68	0.46	0.99	0.53
Pairs	661	661	661	661	661
Sample 3: Geographically closest cointegrated pairs					
Mean	0.53	0.48***	-0.04**	0.44***	-0.01
St. Dev.	0.11	0.07***	0.12	0.09***	0.12
Min	0.19	0.31	-0.31	0.03	-0.44
Max	0.80	0.65	0.26	0.64	0.32
Pairs	54	79	47	88	59
Sample 4: Geographically closest pairs cointegrated in all three periods					
Mean	0.52	0.49	-0.03	0.44***	-0.06***
St. Dev.	0.10	0.06**	0.11	0.06	0.09
Min	0.19	0.36	-0.31	0.30	-0.19
Max	0.80	0.65	0.16	0.56	0.17
Pairs	32	32	32	32	32

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Stars on NLS_c and $PILS_c$ in the Trade War and Post-Trade War columns indicate that the period mean is significantly different from the mean in the preceding period as determined by Welch's t-test. Stars on ΔNLS_c and $\Delta PILS_c$ indicate that the mean change is significantly different from zero as determined by Student's t-test. Stars on St. Dev. indicate that the variance is significantly different from the variance in the preceding period based on an F-test. Because $NLS_c = PILS_c$ in the bivariate case, each cell reports a single value. River terminal discovery equals one minus the crushing plant value.

Table 12: Pre-trade war, trade war, and post-trade war price discovery at soybean crushing plants (robustness: AIC lag selection)

	Pre-Trade War	Trade War		Post-Trade War	
	NLS_c & $PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$	NLS_c & $PILS_c$	ΔNLS_c & $\Delta PILS_c$
Sample 1: All integrated market pairs					
Mean	0.48	0.47**	0.01**	0.42***	-0.06***
St. Dev.	0.08	0.07**	0.12	0.12***	0.17
Min	0.25	0.19	-0.50	0.00	-0.61
Max	0.96	0.70	0.33	0.78	0.38
Pairs	1,944	1,323	1,063	1,735	937
Sample 2: Pairs cointegrated in all three periods					
Mean	0.46	0.47**	0.01*	0.42***	-0.06***
St. Dev.	0.08	0.08	0.13	0.12***	0.16
Min	0.25	0.19	-0.50	0.00	-0.50
Max	0.96	0.70	0.33	0.78	0.38
Pairs	750	750	750	750	750
Sample 3: Geographically closest cointegrated pairs					
Mean	0.52	0.48***	-0.02	0.44***	-0.04**
St. Dev.	0.10	0.07***	0.12	0.11***	0.14
Min	0.32	0.29	-0.45	0.00	-0.60
Max	0.96	0.68	0.27	0.68	0.24
Pairs	63	75	46	99	65
Sample 4: Geographically closest pairs cointegrated in all three periods					
Mean	0.51	0.49	-0.02	0.43***	-0.06***
St. Dev.	0.10	0.08	0.12	0.10	0.10
Min	0.32	0.29	-0.45	0.00	-0.41
Max	0.96	0.68	0.27	0.65	0.24
Pairs	38	38	38	38	38

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Stars on NLS_c and $PILS_c$ in the Trade War and Post-Trade War columns indicate that the period mean is significantly different from the mean in the preceding period as determined by Welch's t-test. Stars on ΔNLS_c and $\Delta PILS_c$ indicate that the mean change is significantly different from zero as determined by Student's t-test. Stars on St. Dev. indicate that the variance is significantly different from the variance in the preceding period based on an F-test. Because $NLS_c = PILS_c$ in the bivariate case, each cell reports a single value. River terminal discovery equals one minus the crushing plant value. Robustness check: lag length selected by AIC rather than BIC.

Table 13: Summary statistics for pre-trade war and post-trade war nearby futures price discovery measures

	Pre-Trade War		Post-Trade War		Δ	
	NLS_f	$PILS_f$	NLS_f	$PILS_f$	NLS_f	$PILS_f$
Sample 1: All integrated market pairs						
Mean	0.36	0.36	0.33***	0.33***	-0.02***	-0.03***
St. Dev.	0.03	0.03	0.05***	0.06***	0.05	0.06
Min	0.29	0.27	0.00	0.00	-0.28	-0.33
Max	0.46	0.50	0.60	0.61	0.17	0.18
Pairs	663	663	1,885	1,885	474	474
Sample 2: Pairs cointegrated in both periods						
Mean	0.36	0.36	0.33***	0.33***	-0.02***	-0.03***
St. Dev.	0.03	0.04	0.04***	0.05***	0.05	0.06
Min	0.29	0.27	0.12	0.09	-0.28	-0.33
Max	0.46	0.50	0.51	0.51	0.17	0.18
Pairs	474	474	474	474	474	474
Sample 3: Geographically closest cointegrated pairs						
Mean	0.35	0.35	0.33***	0.32***	-0.02	-0.03*
St. Dev.	0.02	0.03	0.03**	0.04*	0.05	0.06
Min	0.29	0.27	0.23	0.22	-0.11	-0.15
Max	0.38	0.40	0.45	0.49	0.08	0.08
Pairs	25	25	93	93	19	19
Sample 4: Geographically closest pairs cointegrated in both periods						
Mean	0.34	0.35	0.33*	0.32**	-0.02	-0.03*
St. Dev.	0.02	0.03	0.04**	0.05**	0.05	0.06
Min	0.30	0.29	0.26	0.23	-0.11	-0.15
Max	0.38	0.40	0.43	0.43	0.08	0.08
Pairs	19	19	19	19	19	19

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Stars on Mean in the Post-Trade War columns indicate the mean is significantly different from the corresponding Pre-Trade War mean as determined by Welch's t-test. Stars on Mean in the Δ columns indicate the mean change is significantly different from zero as determined by Student's t-test. Stars on St. Dev. in the Post-Trade War columns indicate that the variance is significantly different from the Pre-Trade War variance based on an F-test. Subscript f denotes price discovery measures for nearby soybean futures. The trade war period is excluded because no market combinations achieved rank-2 cointegration during that period.