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Suggested citation format:

Dillon, K., and Brorsen, B.W. 2026. “Raising the Bar for Conducting Unit Root Tests with Futures Prices.” Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, Chicago, Illinois, April 20-21, 2026. [http://www.farmdoc.illinois.edu/nccc134/paperarchive]

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Paper prepared for the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, 2026.

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Acknowledgements
This research was funded by the A.J. & Susan Jacques Chair, Oklahoma Agricultural Experiment Station, and USDA National Institute of Food and Agriculture, Hatch Project number OKL03170. We are grateful to Glynn Tonsor for his helpful suggestions. The R program used in this study was written with the help of artificial intelligence.

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Practitioner's Abstract

Unit root tests are used to determine whether futures prices or spreads are mean reverting, but data errors, price limits, and market microstructure can produce misleading results. We examine daily live cattle, feeder cattle, September corn, December corn, and a constructed cattle crush spread from 1990 to 2025. Historical prices were validated against multiple data sources, and panel unit root tests were adjusted for price-limit observations and MA(1) microstructure noise. The preferred test does not reject a unit root for any individual futures market. The cattle crush spread shows weak evidence of mean reversion in unadjusted tests, but this result disappears after correcting for microstructure noise. Dropping limit-day observations has little effect, while correcting data errors materially changes the conclusions. If a cattle crush option is developed, the results favor using a Bachelier model.

Key words: cattle crush spread; panel unit root tests; market microstructure; price limits; spread option

Introduction

Conducting unit root tests is a common component of futures market price analysis (McKendree et al. 2024; Coffey 2025). While the most common finding is a failure to reject the null hypothesis of a unit root, the null hypothesis is rejected more often than expected if futures prices truly follow unit root processes (Bowman and Husain 2004).

This study argues that rejecting the null hypothesis is due to weaknesses in the data and statistical methods used. The goal is to raise the bar for the way we conduct unit root tests with futures price data. The issues considered are (i) using panel unit root tests, (ii) errors in the data, (iii) price limits, and (iv) microstructure noise. While the effect of using panel unit root tests is ambiguous, the other three are known to lead to false rejections of the unit root hypothesis. The application considered is the cattle crush and its three components: feeder cattle, fed cattle, and corn.

Soybean crushers can (i) trade all three legs as a single transaction, (ii) buy options directly on the crush margin index, and (iii) trade the composition of the margin via oilshare products. By contrast, cattle feeders must still manually leg into three separate futures contracts with no single-instrument crush trade, no crush margin index, and no options on the spread itself. Testing for unit roots is a precursor to designing a cattle crush options contract.

Commodity futures markets impose daily price limits that prevent prices from moving beyond a fixed band in a single trading session. On limit days, the observed price change may not reflect the full market-clearing move, potentially affecting the distribution of observed returns. We address this by reporting results that exclude limit-hit observations as a robustness check, alongside standard OLS-based tests.

This study describes panel unit root tests that account for daily price limits and microstructure noise. We implement panel extensions of the Im, Pesaran, and Shin (2003) test (hereafter IPS) and the Levin, Lin, and Chu (2002) test (hereafter LLC) with critical values calculated via Monte Carlo methods. We also consider a variant that drops price-limit observations prior to testing and apply a moving-average correction for microstructure noise. The methods are applied to an unbalanced panel of annual contracts covering Live Cattle, Feeder Cattle, September Corn, and December Corn futures, as well as to the Cattle Crush Spread (CCS)—a constructed dollar-valued spread across all four markets. We argue that the no-intercept LLC test with an MA(1) microstructure correction is the preferred specification.

Construction of the Cattle Crush Spread

The cattle crush spread represents the gross margin of cattle feeding and is constructed using futures prices. In the physical market, cattle feeders purchase feeder cattle and corn as inputs and later sell finished live cattle. In the futures market, this relationship is replicated through short (sell) positions in feeder cattle and corn and long (buy) positions in live cattle.

For the August cattle crush, the following positions were used: short August feeder cattle futures, short September and December corn futures, and long February live cattle futures. Because cattle spend approximately 180 days on feed (Peel, 2025), February live cattle futures were chosen to construct the August cattle crush. The hedge ratio for the crush reflects contract size differences and feeding requirements. Following Ingram et al. (2023), who established a ratio of 2 live cattle contracts, 1 feeder cattle contract, and 1 corn contract, the corn contract is further split to reflect the purchasing decisions of a cattle feeder, since not all feed will be purchased upfront, particularly with harvest approaching. The ratio selected for this study therefore consists of 2 February live cattle contracts, 1 August feeder cattle contract, 0.6 September corn contracts, and 0.4 December corn contracts.

With this ratio, the cattle crush spread (CCS_t) is calculated as

$$CCS_t = 2 \times (LC_{t,Feb} / 100 \times 40{,}000) - 1 \times (FC_{t,Aug} / 100 \times 50{,}000) - 0.6 \times (CO_{t,Sep} \times 5{,}000) - 0.4 \times (CO_{t,Dec} \times 5{,}000),$$

where $LC_{t,Feb}$ is the February live cattle futures price at day t (cents/lb), $FC_{t,Aug}$ is the August feeder cattle futures price at day t (cents/lb), and $CO_{t,Sep}$ and $CO_{t,Dec}$ are the September and December corn futures prices at day t (\$/bu). The units of the calculated cattle crush spread are dollars per feeder cattle contract.

A higher cattle crush spread indicates that the expected value of finished cattle is high relative to the combined cost of feeder cattle and feed inputs. A low or negative crush spread implies that input costs are relatively high compared to expected cattle prices. Cattle feeders would hedge by taking a short position in the cattle crush spread contract.

Data and Empirical Procedures

The study is interested in developing an August cattle crush contract and so that dictates the data chosen. For example, the August 2025 cattle crush is defined to consist of short one August 2025 feeder cattle contract, long two February 2026 fed cattle contracts, short 0.6 September 2025 corn contracts, and short 0.4 December corn contracts. Only data from February to August of each year are used since a cattle crush contract is expected to only have volume near maturity. Historical daily settlement prices for live cattle, feeder cattle, and corn futures were collected from the Livestock Marketing Information Center (LMIC). The data were from 1990 to 2025, which provided 35 years of data. Live cattle futures contract units are cents/lb., and the contract size is 40,000 lb. Feeder cattle futures contract units are in cents/lb., and the contract size is 50,000 lb. Corn futures contract units are in $/bu., and the contract size is 5,000 bushels. To identify data errors, LMIC data were compared with the daily closing prices for live cattle, feeder cattle, and corn futures obtained from Barchart and Price-Data.com.

Data Validation

The daily prices were compared across all three sources. Observations were flagged when the difference in daily prices between any of the three sources exceeded $0.10 per bushel for corn and $0.50 per hundredweight for live and feeder cattle. These numeric thresholds were used to capture data entry errors, rather than minor rounding differences.

Inconsistencies were examined and corrected for data that failed the validation test. For instance, during the period of November 17 to November 19, 1997, the LMIC September corn price jumped from $2.88 to $2.08 and then back up to $2.85 the following day. This was marked as a data entry error, as this price jump reflected a change higher than the allowed limit. The Price-Data.com price was $2.87 rather than $2.08. The LMIC dataset was corrected to reflect the Price-Data.com value. This type of data validation was performed for all contract months listed for live cattle futures, feeder cattle futures, and corn futures. Most discrepancies found within the futures data were in the early years when LMIC data was entered manually.

Through this validation process, data entry inconsistencies were corrected. Careful validation of historical price data is important in time-series analysis because data-entry errors or missing observations can create outliers that distort volatility estimates, bias autocorrelation measures, and bias unit root tests toward rejecting unit roots (Haldrup et al. 2005).

The typical approach in time series analysis of futures prices is to string together futures price series to create a continuous series. The problem with this approach is that it assumes that futures contracts in all years converge to the same mean price. Maples and Brorsen (2022) suggest using panel unit root tests, and we follow their approach. Note that past research that splices together futures prices of different maturity months uses futures prices as a proxy for cash prices. What this research does is not wrong. It is just different. Past research whether using cash prices or using futures as a proxy for cash prices for cattle and corn have most often failed to reject the null hypothesis of a unit root (Xu 2018; Mefford and Mallory 2021; Geman and Vergel Eleuterio 2015; Coffey 2025), although Anderson et al. (2026) did reject and Hailu et al. (2015) had mixed findings.

Measurement errors cause the unit-root hypothesis to be over-rejected (Haldrup et al. 2005). Data entry errors and microstructure noise are both forms of measurement error and so result in over-rejection of the unit-root hypothesis. Microstructure noise created by bid-ask bounce will be reduced somewhat because exchanges use settlement prices rather than the last transaction price of the day.

Bounds on prices result in over-rejection of the unit-root hypothesis (Cavaliere and Xu 2014). We address this by reporting results that exclude limit-hit observations as a robustness check and comparing them with the standard OLS-based results. The two approaches yield very similar findings, indicating that price limits are not a major concern for these markets, given the sample size and frequency of limit events.

Identification of Price Limit Events

Historical daily price limits for corn, feeder cattle, and live cattle were compiled from CME rulebooks and official exchange releases. Limit levels vary over time and may expand under specific conditions. For each contract and trading day, a limit flag was created, where +1 denotes an upside limit hit, −1 denotes a downside limit hit, and 0 indicates that no limit was reached.

Limit detection was based on the daily price change relative to the active price limit for that date. The daily change for each contract was calculated as $\Delta P_t = P_t - P_{t-1}$, where P_t is the settlement price on day t. A limit event was recorded when the absolute value of the daily price change was greater than or equal to the active limit level for that day, allowing a small numerical tolerance of 0.001 to avoid rounding errors. To prevent contract rollover effects from being classified as limit hits, rollover dates were identified for each commodity and contract month, and the daily price change on those dates was set to missing before the flagging rules were applied.

Panel Unit Root Framework

Let y_{it} denote the log-price (or level, for the CCS spread) of futures contract i on day t, where $i = 1, \ldots, N$ indexes contract-years, and $t = 1, \ldots, T_i$ indexes trading days within the contract. For each contract we estimate the Dickey-Fuller (DF) regression

$$(1) \quad \Delta y_{it} = \alpha_i + \phi_i y_{i,t-1} + \varepsilon_{it},$$

where α_i is a contract-specific intercept, ϕ_i is the mean-reversion coefficient of interest, and $\varepsilon_{it} \sim$ i.i.d. $N(0, \sigma_i^2)$ under the null hypothesis. The null hypothesis is H_0: $\phi_i = 0$ for all i, against the alternative H_1: $\phi_i < 0$ for some i. A no-intercept version sets $\alpha_i = 0$, which is appropriate when prices are expected to follow a driftless random walk within a contract year. Note that an augmented test is not used since lagged values should not be significant in an efficient futures market (except in the case of microstructure noise).

IPS and LLC Panel Statistics

The IPS statistic (Im, Pesaran, and Shin 2003) standardizes the cross-sectional average of the per-contract t-statistics for $\hat{\phi}_i$ as follows:

$$(2) \quad W = \sqrt{N} \cdot [\bar{\tau} - \overline{E}(\tau)] / \sqrt{\overline{Var}(\tau)},$$

where $\bar{\tau} = N^{-1} \Sigma_i \tau_i$ is the cross-sectional mean of contract-level t-statistics, and $\overline{E}(\tau)$ and $\overline{Var}(\tau)$ are the cross-sectional averages of the contract-specific Monte Carlo moments of the t_i-statistic under H_0. Under H_0 and as $\min(N, T) \to \infty$, $W \Rightarrow N(0, 1)$. The one-sided p-value is denoted as $\Phi(W)$.

The LLC statistic (Levin, Lin, and Chu 2002) imposes the homogeneity restriction $\phi_i = \phi$ for all i and estimates a single pooled coefficient. The pooled t-statistic for H0: $\phi = 0$ is calibrated against a Monte Carlo null distribution rather than LLC's asymptotic correction tables, because the latter were derived for large balanced panels and may not hold for the heterogeneous-variance specification with unequal contract lengths used here.

MA(1) Microstructure Correction

Bid-ask bounce and other market microstructure effects induce negative serial correlation in daily price changes of the form $\Delta y_t = \varepsilon_t + \theta\varepsilon_{t-1}$ with $\theta \in (-1, 0)$ (Roll 1984; French and Roll 1986). If ignored, this MA(1) component inflates the variance of $\bar{\tau}$ in small samples and causes the i.i.d. null distribution to be too liberal, overstating significance. Following the approach of Bai and Perron (2003) for nuisance parameter estimation in unit root tests, we estimate θ from the pooled lag-1 sample autocorrelation of the residuals:

(3) $\hat{\rho}_1 = \Sigma_{i,t}\, \Delta\hat{y}_{it}\, \Delta\hat{y}_{i,t-1} \,/\, \Sigma_{i,t}\, (\Delta\hat{y}_{it})^2$,

where $\Delta\hat{y}_{it} = \Delta y_{it} - \overline{\Delta y}$. The MA(1) parameter satisfies $\rho_1 = \theta/(1 + \theta^2)$. When $\hat{\rho}_1 < 0$, we invert this relationship to obtain $\hat{\theta}$ selecting the root closest to zero (an invertible solution). The Monte Carlo null distribution is then simulated under an MA(1) data-generating process with innovations $\varepsilon_t + \hat{\theta}\varepsilon_{t-1}$ instead of white noise. This bootstrap is parametric in the sense of Davison and Hinkley (1997, Ch. 4): data are generated from a fully specified parametric model, with the test statistic recomputed for each replication. The moving average parameter is an estimated parameter, and given that our test statistics are asymptotically pivotal, a double bootstrap is not needed.

Why LLC with MA(1) Correction Is the Preferred Test

The LLC test with MA(1) correction is favored as the primary specification.

First, the LLC test has higher power against the alternative that all contracts share a common mean-reversion speed. As shown by Levin, Lin, and Chu (2002) and confirmed in Monte Carlo studies by Breitung (2000), imposing homogeneity of ϕ under the alternative concentrates power in a single degree of freedom rather than dispersing it across N separate contract-level tests. When mean reversion is genuine—as in commodity spreads that are bounded by arbitrage—the homogeneous alternative is economically reasonable and the power advantage of LLC over IPS is substantial.

Second, ignoring the MA(1) microstructure noise inflates the null variance of the test statistic. The MA(1) correction calibrates the null distribution to the actual serial correlation present in the data, producing correctly-sized tests. In the present application, estimated microstructure noise is small: $\hat{\theta} = -0.012$ for live cattle, $\hat{\theta} = -0.077$ for the Cattle Crush Spread, and $\hat{\theta} = 0$ for all other series. The MA(1) correction therefore has negligible impact on the individual commodity markets but does affect the CCS inference.

Simulation of Null Distributions

All null distributions are obtained by parametric bootstrap (Davison and Hinkley 1997). For each of B = 5,000 replications, we generate an N-dimensional random walk panel under H0 with the same panel dimensions as the observed data. For the MA(1) variant, the innovations follow $\varepsilon_t + \hat{\theta}\varepsilon_{t-1}$. The drop-limits variant excludes all flagged observations before estimation; the uncensored variant uses the full sample. Each replication fits all estimators to the simulated panel; the empirical distributions of the resulting test statistics serve as the reference null distributions for computing p-values.

The IPS moments $E(\tau_i)$ and $Var(\tau_i)$ are estimated as the cross-replication mean and variance of the simulated per-contract t_i-statistics. The LLC p-value is the empirical proportion of bootstrap replications in which the pooled t-statistic is more extreme than the observed value. Computational efficiency is achieved by parallelizing replications across available CPU cores.

Results

Tables 1, 2, and 3 present the panel unit root test results for live cattle, feeder cattle, September corn, December corn futures, and the Cattle Crush Spread over 1990–2025. Table 1 presents the tests on the original, uncorrected data. Tables 2 and 3 use data that have been validated and corrected for errors. Comparison of Table 1 with Tables 2 and 3 illustrates the importance of careful data validation. Table 2 reports the IPS W-bar statistic with and without a contract-specific intercept. Table 3 reports the LLC adjusted t* statistic in four variants: standard OLS (uncensored), OLS with MA(1) microstructure correction, and both variants after dropping limit-hit observations. All tests are one-sided against the alternative of mean reversion.

For the IPS test with a contract-specific intercept (Table 2), only the Cattle Crush Spread rejects the unit root null ($W = -4.305$, $p < 0.001$). The four individual commodity markets fail to reject: live cattle ($W = -0.600$, $p = 0.274$), feeder cattle ($W = 0.028$, $p = 0.511$), September corn ($W = 2.628$, $p = 0.996$), and December corn ($W = 2.229$, $p = 0.987$). As discussed in the methodology, however, the with-intercept specification captures within-year mean reversion toward the annual contract mean, which is expected by construction and does not constitute evidence of true, long-run mean reversion.

Removing the contract-specific intercept reverses the picture for all individual markets. For live and feeder cattle, the no-intercept IPS statistics become strongly positive ($W = 3.571$, $p > 0.999$ and $W = 5.766$, $p > 0.999$, respectively), providing support for the unit root. The corn markets yield $W = -1.010$ ($p = 0.156$) and $W = -0.319$ ($p = 0.375$) for September and December corn, also failing to reject. The Cattle Crush Spread remains significant under the no-intercept specification ($W = -2.160$, $p = 0.015$), the only series showing evidence of mean reversion in the IPS framework.

The LLC results (Table 3) are consistent with the no-intercept IPS findings for individual commodity markets. All four uncensored LLC statistics are positive and well below the significance threshold: 0.953 (live cattle, $p = 0.878$), 0.262 (feeder cattle, $p = 0.693$), 0.094 (September corn, $p = 0.629$), and 0.349 (December corn, $p = 0.718$). The MA(1) correction has negligible impact on the individual markets since estimated serial correlation is trivial ($\hat{\theta} = -0.012$ for live cattle, $\hat{\theta} = 0$ for all others). For the Cattle Crush Spread, the uncensored LLC statistic is -2.089 ($p = 0.034$), which is significant at the 5% level. However, applying the MA(1) correction ($\hat{\theta} = -0.077$) raises the p-value to 0.119, eliminating statistical significance at conventional levels.

Dropping limit-hit observations before testing produces results nearly identical to the uncensored specification for all individual commodities: statistics shift by at most 0.08 in absolute value and p-values by less than 0.02. For the Cattle Crush Spread, the drop-limits t* is −2.220 (p = 0.025), slightly more negative than the uncensored result; after the MA(1) correction, the p-value is 0.088, again falling short of the 5% threshold. The overall conclusion is robust to the treatment of price limits: there is no statistically significant evidence of mean reversion in any of the four individual futures markets at the 5% level in any specification. The Cattle Crush Spread shows borderline evidence of mean reversion, which disappears once microstructure noise is considered.

Conclusion

This study contributes to the literature on unit root testing in commodity futures markets by addressing four potential sources of over-rejection: panel structure, data-entry errors, price limits, and microstructure noise. Applied to live cattle, feeder cattle, September corn, and December corn futures from 1990 to 2025, our preferred specification—the LLC test with an MA(1) microstructure correction—consistently fails to reject the null hypothesis of a unit root for all four individual markets. The Cattle Crush Spread shows borderline mean reversion until the MA(1) correction is added. These findings hold across all specifications and are robust to the exclusion or inclusion of price-limit observations.

The choice of test specification matters considerably. First, the IPS test with a contract-specific intercept fails to reject the unit root for the four individual commodity markets but spuriously finds mean reversion for the Cattle Crush Spread due to within-year price reversion that is expected by construction. The more appropriate no-intercept specification and the LLC test agree: no individual futures market shows significant mean reversion. Second, dropping limit-hit observations leaves test statistics and p-values essentially unchanged. Third, careful data validation matters: data entry errors in the early years of the LMIC dataset can cause spurious rejections of the unit root hypothesis. Fourth, the MA(1) correction for microstructure noise has a negligible impact on individual commodity markets but does affect the CCS inference, reducing its borderline significance below conventional thresholds.

The failure to reject a unit root is consistent with weak-form market efficiency (Bowman and Husain 2004) and supports the theoretical prediction that arbitrage-free futures prices follow martingale processes (Gibson and Schwartz 1990). For practitioners, unit root behavior implies that price changes, rather than levels, should be used in forecasting models. These results favor using the Bachelier model (Seok et al. 2018) in designing an option contract on the crush margin. Our future research will extend this study to simulate and test the Bachelier model.

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Table 1. Unit Root Tests on Original Data

Commodity	IPS Statistic	IPS p-value	IPS Decision at 5%	LLC Statistic	LLC p-value	LLC Decision at 5%
Live Cattle	-2.8012	0.0025	Reject	-1.4861	0.0686	Fail to Reject
Feeder Cattle	-2.4273	0.0076	Reject	-0.3167	0.3757	Fail to Reject
Sep Corn	1.0239	0.8471	Fail to reject	2.3147	0.9897	Fail to Reject
Dec Corn	0.9842	0.8375	Fail to reject	2.4705	0.9933	Fail to reject
CCS	-9.3800	<0.0001	Reject	-4.9272	<0.0001	Reject

Note: The original data is the uncorrected dataset pulled directly from LMIC.

Table 2. Im-Pesaran-Shin (IPS) Panel Unit Root Tests

	With Intercept		Without Intercept	
Commodity	**W-bar**	**p-value**	**W-bar**	**p-value**
Live Cattle (Feb)	−0.600	0.274	3.571	>0.999
Feeder Cattle (Aug)	0.028	0.511	5.766	>0.999
Corn (Sep)	2.628	0.996	−1.010	0.156
Corn (Dec)	2.229	0.987	−0.319	0.375
Cattle Crush Spread	−4.305	<0.001	−2.160	0.015

Note: The W-bar statistic tests H_0: all panels contain a unit root against H_1: some panels are stationary (Im, Pesaran, and Shin, 2003). Lags = 0. Sample: 1990–2025 (35 years).

Table 3. Levin-Lin-Chu (LLC) Panel Unit Root Tests

	Uncensored		Uncensored MA(1)		Drop Limits		Drop Limits MA(1)	
Commodity	**t***	**p-value**	**t***	**p-value**	**t***	**p-value**	**t***	**p-value**
Live Cattle (Feb)	0.953	0.878	0.953	0.890	0.971	0.882	0.971	0.894
Feeder Cattle (Aug)	0.262	0.693	0.262	0.693	0.229	0.677	0.229	0.677
Corn (Sep)	0.094	0.629	0.094	0.629	0.175	0.659	0.175	0.659
Corn (Dec)	0.349	0.718	0.349	0.718	0.542	0.782	0.542	0.782
Cattle Crush Spread	−2.089	0.034	−2.089	0.119	−2.220	0.025	−2.220	0.088

Note: The adjusted t* statistic tests H_0: common unit root process (Levin, Lin, and Chu, 2002). Lags = 0. Sample: 1990–2025 (35 years). MA(1) correction uses the estimated θ parameter: Live Cattle (Feb) θ = −0.012; Cattle Crush Spread θ = −0.077; all others θ = 0. Drop Limits: observations at price limits were excluded prior to testing.