DIVERSIFICATION WITHIN AGRICULTURAL ETFS: EVIDENCE ON RETURN, VOLATILITY AND DOWNSIDE RISK[1]

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Abstract

This study examines whether broader agricultural exposure is associated with differences in the return and risk characteristics of agricultural exchange-traded funds (ETFs). The analysis compares a monthly-rebalanced equal-weighted portfolio of four single-commodity ETFs (SOYB, WEAT, CANE, and CORN) with the Invesco DB Agriculture Fund (DBA) over April 2016 - March 2026. DBA returns are evaluated on a total-return basis with cash distributions reinvested. Daily returns are used to compare mean performance, volatility, return distributions, and downside risk, while monthly returns are used to assess compounded performance and risk-adjusted outcomes. Average daily returns do not differ significantly, whereas the single-commodity portfolio exhibits higher volatility and more adverse, 95% and 99% downside risk. DBA also generates higher terminal wealth and a smaller maximum drawdown. Alternative weighting tests confirm lower DBA volatility under equal, inverse-volatility, and minimum-variance constructions, although the gap narrows under minimum-variance allocation.

Key words: Agricultural ETFs, diversification, return and risk analysis, volatility, downside risk.

JEL[5]: Q14, G11, G12

1 The research presented in this paper was funded by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia under contract no. 451-03-136/2025-03

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5 Article info: Original article, Received: 22nd April 2026, Accepted: 7th September 2026.

Introduction

Exchange-traded funds (ETFs) have become one of the most prominent financial innovations in modern capital markets, providing investors with transparent, low-cost, and easily tradable access to a wide range of asset classes. Their rapid expansion since the 1990s, particularly following the global financial crisis, reflects their ability to combine diversification, liquidity, and operational simplicity within a single investment vehicle. As a result, ETFs are increasingly used not only for passive investment strategies, but also for tactical allocation and portfolio diversification across different market segments.

Within the broader ETF universe, commodity-based ETFs occupy a distinctive position, as they offer indirect exposure to commodity markets without requiring direct participation in spot, or futures trading. Agricultural ETFs represent a particularly specific subset of this segment. Their performance is shaped by movements in underlying commodity prices, along with structural features, such as futures-based replication, contract rolling strategies, and exposure to commodity-specific risks, including seasonality, weather conditions, and supply shocks. These characteristics make agricultural ETFs inherently different from traditional financial assets and suggest that their evaluation requires a multidimensional perspective going beyond simple return comparisons.

An important, yet relatively underexplored, aspect of agricultural ETFs is the distinction between concentrated exposure to individual agricultural products and broader exposure across several agricultural commodity markets. This distinction is particularly relevant from an investment perspective because broader exposure may alter overall volatility and downside risk. At the same time, differences between funds can also reflect futures-contract selection and product design, so the effect of diversification should be evaluated with these structural differences in mind.

Against this background, the objective of this study is to compare the return and risk characteristics of a portfolio of single-commodity agricultural ETFs, with a broadly diversified agricultural ETF benchmark. The analysis focuses on average returns, overall volatility, downside risk, long-horizon performance, and robustness to alternative portfolio weighting. It is guided by two main research questions. The first examines whether the single-commodity portfolio and the diversified benchmark differ in terms of average returns. The second evaluates whether broader agricultural exposure is associated with differences in volatility and downside risk, capturing both overall return dispersion and exposure to extreme negative outcomes.

The remainder of the paper is structured as follows: Section two reviews the relevant literature and positions the study within the broader research context. Section three presents the data and methodology, including benchmark selection and construction, long-horizon performance measures, and weighting robustness tests. Section four reports the empirical results for daily returns, volatility, downside risk, cumulative performance, monthly-frequency robustness, and alternative portfolio specifications. Section five discusses the findings and their implications. Finally, section six concludes.

Literature Review

Following the launch of the first modern ETF in Canada in 1990, the global ETF market expanded significantly, gaining particular momentum after the 2008 financial crisis, as investors increasingly turned to transparent, low-cost, and index-based investment vehicles. This rapid growth reflects the core characteristics that have made ETFs attractive to both institutional and retail investors, including intraday tradability, relatively low management costs, diversification benefits, and broad accessibility across asset classes and market segments. As a result, ETFs have become important both as practical investment instruments, and as a major subject of academic research. Recent review evidence suggests that the ETF literature is mainly organized around several recurring themes, including tracking error, volatility, liquidity, price discovery, and broader risk-return issues (Joshi, Dash, 2024).

Within this general field, commodity ETFs occupy a distinctive position because they provide investors with exchange-traded access to commodity markets without requiring direct participation in spot or futures trading. Earlier studies also indicate that exchange-traded products may affect the behaviour of underlying commodity markets through liquidity and volatility channels, implying that commodity ETFs should be examined as portfolio instruments, as well as products with wider market implications (Corbet, Twomey, 2014). Agricultural ETFs constitute a particularly distinct segment of the commodity ETF universe. In contrast to conventional equity ETFs, agricultural ETFs are typically based on futures-linked exposure, meaning that their performance depends not only on movements in underlying agricultural prices, but also on tracking quality and other product-specific characteristics, such as replication method and leverage (Perera et al., 2022; Stewart et al., 2023). Moreover, these issues are especially important in agricultural markets, where weather conditions, harvest outcomes, seasonality, crop yields, and supply-side shocks strongly influence prices. Consequently, evaluating agricultural ETFs requires a more comprehensive analytical framework than a simple comparison of nominal returns, since both fund structure and commodity-market dynamics can materially affect observed

performance. Accordingly, this view is consistent with the existing commodity ETF literature, which emphasizes that performance varies across market conditions, and that risk-adjusted outcomes may differ substantially from raw return patterns (Hadad et al., 2024). Within this context, the existing literature on agricultural exchange-traded products can be broadly grouped around three related issues: tracking efficiency and product design, risk heterogeneity within the agricultural ETF segment, and the overall market environment in which these instruments operate.

First strand of the literature focuses on tracking efficiency and product design. Stewart et al. (2023) offer a particularly relevant contribution to the literature by examining the tracking performance of U.S. agricultural and energy exchange-traded products. Their results indicate that tracking errors are primarily driven by arbitrage, highlighting the role of market frictions in shaping tracking efficiency. Study also covers both single-commodity and commodity-sector products, thereby broadening the empirical scope of exchange-traded exposure in agricultural and energy markets (Stewart et al., 2023). Nevertheless, the analysis remains focused on tracking efficiency, and does not extend to a comprehensive comparison of returns, volatility, and investment efficiency across different categories of agricultural ETFs. Therefore, question of whether diversified and single-commodity agricultural ETFs differ systematically in their overall investment characteristics remains insufficiently explored. Related line of research is provided by Perera et al. (2022), who examine agricultural exchange-traded commodities (ETCs), and show that tracking error is time-varying rather than constant. Results suggest that tracking performance depends on the volatility of underlying commodity prices and is influenced by replication method and leverage. Although the study focuses on ETCs rather than ETFs, it remains informative for the present analysis, because it shows that structural product characteristics may shape performance beyond the underlying commodity exposure. In other words, differences in observed outcomes may arise from the specific commodity exposure, as well as from the product's design (Perera et al., 2022). This perspective is also consistent with more recent evidence suggesting that the expected returns of commodity ETFs should be assessed on the basis of the ETF's underlying assets and replication strategy, rather than estimated solely from ETF market prices using conventional expected-return models (Cortazar et al., 2024).

Second strand of the literature emphasizes the internal heterogeneity of agricultural ETFs from a risk perspective. Kaminskyi and Nehrey (2019) treat agricultural ETFs as a distinct investment class, and emphasize that their risk-return characteristics differ from those of conventional financial assets, because they are shaped by agricultural factors, such as weather conditions and crop yields. Kaminskyi et al. (2020) extend this perspective by offering a more comprehensive risk analysis and explicitly classifying

agricultural ETFs into distinct groups, thereby highlighting the internal heterogeneity within the agricultural ETF segment. Classification logic is highly relevant for a comparative framework that distinguishes diversified agricultural ETFs from single-commodity agricultural ETFs, since it supports the argument that agricultural funds should not be analysed, as a single homogeneous category (Kaminskyi, Nehrey, 2019; Kaminskyi et al., 2020).

Third strand of the literature highlights the broader market environment in which agricultural exchange-traded products are embedded. Chang et al. (2019) show that agriculture and energy-related spot, futures, and ETF prices are connected through volatility spill-overs, suggesting that ETF behaviour should be interpreted within a broader transmission environment, rather than in isolation. In parallel, extensive evidence from commodity ETFs suggests that they underperformed U.S. equities over the long run, though they exhibited greater resilience during turbulent periods such as the COVID-19 crisis (Hadad et al., 2024). Together, these findings reinforce the idea that exchange-traded commodity products should be evaluated by average returns along with volatility, downside risk, and sensitivity to market regimes (Chang et al., 2019; Hadad et al., 2024). More broadly, this strand of the literature indicates that the performance of agricultural exchange-traded products cannot be assessed in isolation from wider cross-market linkages and evolving market conditions.

A broader strand of the commodity-allocation literature provides useful context for interpreting diversification within agricultural markets. Commodity futures have long been considered potential portfolio diversifiers because individual commodity returns are imperfectly correlated and can behave differently from conventional financial assets (Gorton, Rouwenhorst, 2006; Erb, Harvey, 2006). However, subsequent evidence shows that diversification benefits are neither uniform, nor guaranteed. Cheung and Miu (2010) find that the gains from commodity futures depend on market conditions and investor characteristics, while Daskalaki and Skiadopoulos (2011) question whether in-sample diversification benefits persist out of sample. Bessler and Wolff (2015) further show that portfolio effects vary considerably across commodity sectors and allocation strategies, and Ruano and Barros (2022) emphasize that diversification benefits are time-dependent, and particularly relevant for loss-averse investors. These findings motivate an assessment that considers volatility and downside risk in addition to average returns.

The portfolio-construction literature also indicates that diversification results can depend on the weighting rule used to combine assets. Equal-weighting provides a transparent benchmark, and has often proved difficult to perform out of sample when estimation error is substantial (DeMiguel et al., 2009). At the same time, minimum-variance allocation can materially reduce portfolio risk when covariance

information is informative (Clarke et al., 2006), while long-only constraints can improve the stability of estimated minimum-variance portfolios (Jagannathan, Ma, 2003). Consequently, conclusions based on a single weighting scheme should be complemented by alternative risk-based allocations.

Despite these valuable contributions, the literature remains fragmented in ways that leave room for further research. Existing studies show that product design matters for tracking quality, agricultural exchange-traded products are internally heterogeneous, commodity diversification benefits can vary across market conditions, and portfolio construction itself may affect measured risk reduction. Relatively limited attention has been devoted to a direct comparison between a portfolio of single-commodity agricultural ETFs, and a broad agricultural ETF benchmark, using a common framework that combines average returns, volatility, return distributions, downside risk, long-horizon performance, and weighting robustness. The present study addresses this gap by comparing a portfolio of four single-commodity crop ETFs with DBA, within a common framework that combines average returns, volatility, return distributions, downside risk, long-horizon performance, and weighting robustness.

Methodology and Data

Empirical analysis is based on five agricultural exchange-traded funds. Four funds provide single-commodity exposure: SOYB (soybeans), WEAT (wheat), CANE (sugar), and CORN (corn). DBA (Invesco DB Agriculture Fund) is used as the diversified agricultural benchmark. The sample covers April 1, 2016 - March 31, 2026, and is based on daily closing prices obtained from NASDAQ (Nasdaq, n.d.). TAGS is excluded from the empirical comparison because it is a fund-of-funds that allocates approximately 25% of its assets to each of CORN, SOYB, CANE, and WEAT, and is generally rebalanced daily (Teucrium Commodity Trust, 2026). Including TAGS would therefore create a mechanically nested comparison. DBA remains partially exposed to the same crop markets, but also includes cocoa, coffee, cotton, livestock, Kansas City wheat, and, under the methodology introduced in November 2025, soybean meal and soybean oil. Under the pre-November 2025 base weights, corn, soybeans, CBOT wheat, and sugar represented 43.75% of the DBA index. Their corresponding weight was 39.01% at December 31, 2025 (Invesco DB Agriculture Fund, 2023; 2026). DBA is consequently interpreted as a broader agricultural benchmark, rather than a fully non-overlapping portfolio. All data processing and empirical analysis were performed using Stata 15 and Python 3.

ETF performance is evaluated using logarithmic returns:

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

Where, r(i, t) denotes the log return of ETF i in period t, and P(i, t) and P(i, t-1) are closing prices in the current and previous period, respectively. For the four Teucrium funds, no cash distributions were identified during the sample, so these price changes represent the relevant investor return series.

DBA requires an additional adjustment, because it made cash distributions during the observation period. Its simple total return is therefore calculated as R(TR, DBA, t) = [P(DBA, t) + D(t) - P(DBA, t-1)] / P(DBA, t-1), where, D(t) denotes the cash distribution per share on the ex-distribution date. Official Invesco notices identify distributions of USD 0.17994, 0.25717, 0.09643, 0.96045, 1.08408, and 0.91237 per share in 2018, 2019, 2022, 2023, 2024, and 2025, respectively. These distributions are assumed to be reinvested immediately, without taxes or transaction costs, and the corresponding DBA log return is ln[1 + R(TR, DBA, t)], (Invesco, 2018-2025). Teucrium fund disclosures state that CORN, SOYB, CANE, and WEAT generally do not distribute dividends to shareholders (Teucrium Trading, n.d.).

Analysis proceeds at two levels. First, descriptive statistics are reported for each ETF, and for the single-commodity portfolio, including mean return, standard deviation, minimum and maximum values, skewness, and kurtosis. Second, formal time-series inference compares the single-commodity portfolio with DBA. Variance is interpreted as a measure of total risk within the mean-variance framework of Markowitz (1952). For each ETF i, sample mean return is computed as:

$$\bar{r}_i = \frac{1}{T}\sum_{t=1}^{T} r_{i,t}$$

The sample standard deviation measures volatility:

$$\sigma_i = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(r_{i,t}-\bar{r}_i\right)^2}$$

The baseline single-commodity portfolio is initialized with equal 25% weights in SOYB, WEAT, CANE, and CORN, and rebalanced monthly. Between rebalancing dates, weights are allowed to drift with relative asset performance. Because log returns are not additive across assets, portfolio returns are first constructed from

simple ETF returns using lagged portfolio weights, and then transformed into log returns for formal inference:

$$R_t^S = \sum_{i=1}^{4} w_{i,t-1} R_{i,t}, \qquad r_t^S = \ln(1 + R_t^S)$$

Here, R(S, t) is the simple return on the single-commodity portfolio, R(i, t) is the simple return on ETF i, and w(i, t-1) is the weight carried into period t. The log portfolio return r(S, t) is used in the daily inferential tests. DBA is compared using its distribution-adjusted total-return series, rather than the unadjusted change in closing price.

Equal-weighting is retained as the baseline, because it provides a transparent 1/N benchmark and avoids estimating expected returns (DeMiguel et al., 2009). Robustness to alternative risk-based weighting is examined separately below.

The descriptive measures provide an initial comparison of the return and risk profiles of the individual ETFs, the single-commodity portfolio, and DBA.

The daily return differential is defined as:

$$d_t = R_{S,t} - R_{D,t}$$

To assess whether there is a statistically significant difference in average daily returns, the study evaluates the null hypothesis H0: E(d_t)=0, against H1: E(d_t)≠0, using the constant-only regression specification:

$$d_t = \alpha + \varepsilon_t$$

Where, alpha captures the mean return differential between the single-commodity portfolio and DBA. The conventional t-test is reported as a benchmark. Heteroskedasticity-robust standard errors are also reported, while the main time-series inference uses heteroskedasticity- and autocorrelation-consistent (HAC) standard errors based on the Newey West (1987) estimator with five daily lags. A Wilcoxon signed-rank test evaluates the median differential. Differences in the overall shape of the two return distributions are additionally summarized by the two-sample Kolmogorov-Smirnov distance. Because the two strategies are observed contemporaneously, and are economically dependent, conventional KS p-values are not used for inference. The KS statistic is interpreted descriptively as the maximum distance between the empirical cumulative distribution functions.

As an additional robustness check for the mean return differential, a stationary bootstrap with 5,000 replications, and an expected block length of five trading days is applied. This procedure preserves short-run time-series dependence, while avoiding a parametric distributional assumption (Politis, Romano, 1994).

To examine whether return volatility is systematically higher for the single-commodity portfolio than for DBA, the study evaluates H0: Var(r (S, t)) = Var(r (DBA, t)) against the one-sided economic alternative that the single-commodity variance is higher. A classical variance-ratio F-test is reported as a benchmark. Given the non-normality and volatility clustering commonly observed in financial returns (Cont, 2001), primary inference is based on squared demeaned returns:

$$v_{S,t} = (R_{S,t} - \bar{R}_S)^2, v_{D,t} = (R_{D,t} - \bar{R}_D)^2$$
$$q_t = v_{S,t} - v_{D,t}$$
$$q_t = \beta + u_t$$

Where beta captures the average difference in squared deviations between the two-return series. A positive and statistically significant beta indicates higher variance for the single-commodity portfolio. Heteroskedasticity-robust and Newey-West HAC standard errors are reported, with the latter treated as the main inference.

To complement the analysis of overall return variability, the study evaluates downside risk using historical Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). Historical VaR is computed at both, the 95% and 99% confidence levels, as the empirical 5th and 1st percentiles of the daily log-return distribution. This non-parametric approach is appropriate given the observed excess kurtosis, and does not impose a normality assumption.

$$VaR_{0.95} = \inf\{r: P(R \leq r) \geq 0.05\}$$

The displayed expression defines the 95% case. The same historical procedure is repeated at the 99% confidence level using the empirical 1st percentile.

Conditional Value-at-Risk (CVaR), also referred to as Expected Shortfall, is computed as the average return conditional on returns falling below the corresponding VaR threshold:

$$CVaR_{0.95} = E[R \mid R \leq VaR_{0.95}]$$

VaR identifies the threshold associated with extreme downside outcomes, whereas CVaR captures the expected magnitude of returns once that threshold is breached. CVaR therefore provides information about the severity of losses beyond the VaR cutoff (Rockafellar, Uryasev, 2002; Acerbi, Tasche, 2002). The CVaR/VaR ratio is also reported as a relative indicator of tail severity.

Comparing VaR and CVaR between the single-commodity portfolio and DBA establishes whether the daily volatility difference is accompanied by differences in downside exposure.

The daily analysis is complemented by a long-horizon perspective, based on monthly simple total returns. Monthly returns are obtained by compounding the daily strategy returns within each calendar month, so DBA cash distributions are incorporated, and reinvested in the terminal-wealth calculation. For each strategy, the analysis reports terminal wealth from an initial investment of one-dollar, cumulative return, annualized geometric return, annualized volatility, and maximum drawdown. Maximum drawdown is calculated from the daily cumulative total-return wealth path. Risk-adjusted performance is evaluated using the Sharpe and Sortino ratios. The Sharpe ratio uses the monthly 3-month U.S. Treasury constant-maturity rate (GS3M) as the risk-free benchmark, converted from the reported annual yield to a monthly effective rate (Board of Governors of the Federal Reserve System, n.d.). The Sortino ratio uses a minimum acceptable return of zero, consistent with the downside-risk framework in which negative periodic returns represent shortfall outcomes (Sortino, Price, 1994).

Differences in Sharpe and Sortino ratios are evaluated using a paired stationary bootstrap, with 5,000 replications, and an expected block length of six months. The paired resampling preserves contemporaneous dependence between the two strategies and the risk-free rate series, while the stationary-bootstrap construction allows blocks of random length and accommodates serial dependence in monthly returns (Politis, Romano, 1994; Ledoit, Wolf, 2008).

As an additional frequency robustness check, the principal mean-return, distributional-distance, and volatility comparisons are repeated using monthly log total returns. This lower-frequency analysis reduces the influence of short-horizon noise, and tests whether the direction of the daily results persists when returns are aggregated over longer intervals. As in the daily analysis, the monthly KS statistic is reported descriptively without a conventional p-value, because the two strategies are contemporaneously dependent.

Finally, the sensitivity of the results to portfolio construction is assessed using two alternatives to the equal-weighted benchmark. Inverse-volatility weights and long-only global minimum-variance weights are estimated at each month-end using the preceding 252 daily observations, and are applied during the following month. The procedure is strictly backward-looking and therefore avoids look-ahead bias. Inverse-volatility weights allocate more capital to lower-volatility ETFs, while the minimum-variance portfolio uses the estimated covariance

matrix subject to non-negative weights summing to one (Clarke et al., 2006; Jagannathan, Ma, 2003).

$$w_{i,m}^{IV} = \frac{1/\hat{\sigma}_{i,m}}{\sum_{j=1}^{4} 1/\hat{\sigma}_{j,m}}$$

$$\min_{\mathbf{w}_m} \mathbf{w}_m{}' \hat{\Sigma}_m \mathbf{w}_m \quad \text{s.t.} \quad \mathbf{1}'\mathbf{w}_m = 1,\ w_{i,m} \geq 0$$

Because a full 252-day estimation window is required, the alternative-weighting robustness sample runs from April 2017 to March 2026. All alternative strategies are rebalanced monthly and compared with DBA over the same common period. Historical AUM weighting is not used, because it would introduce investor-flow and fund-size variation into a test intended to isolate sensitivity to return-based portfolio construction.

Results

Descriptive statistics

Table 1. reports descriptive statistics for the four single-commodity ETFs, the monthly-rebalanced single-commodity portfolio, and DBA. Average daily returns are economically small across the four single-commodity funds. SOYB records a small positive mean return, WEAT and CORN have mildly negative means, and CANE is close to zero.

Table 1. Descriptive Statistics of ETF Returns

Variable	Mean	St. Dev.	Min	Max	Skew.	Kurtosis
SOYB	0.000116	0.010773	-0.0659	0.0552	-0.179	5.855
WEAT	-0.000259	0.016747	-0.1001	0.1450	0.572	8.203
CANE	0.000002	0.013728	-0.0680	0.0527	-0.009	3.823
CORN	-0.000038	0.012292	-0.0645	0.0679	-0.023	6.196
Single-commodity portfolio	-0.000003	0.009801	-0.0497	0.0481	0.048	5.105
DBA (total return)	0.000175	0.008277	-0.0499	0.0298	-0.292	4.976

Source: Authors' calculations.

The single-commodity portfolio has an average daily log return of -0.000003, compared with 0.000175 for DBA after incorporating cash distributions. At the descriptive level, DBA therefore records the higher average return, although formal inference is required to determine whether the difference is statistically distinguishable from zero.

Dispersion measures reveal clearer differences. WEAT has the highest individual standard deviation (0.016747), whereas DBA has the lowest (0.008277). The monthly-rebalanced single-commodity portfolio has a daily standard deviation of 0.009801, which remains above the DBA benchmark. All series display kurtosis above the normal benchmark of three, with particularly pronounced tail thickness for WEAT. These features support the use of robust time-series inference and explicit downside-risk measures.

The distributional statistics also show that the comparison cannot be reduced to mean returns alone. The single-commodity portfolio is nearly symmetric, while DBA exhibits modest negative skewness. Both portfolio series are leptokurtic. Accordingly, differences in dispersion and tail behaviour are examined explicitly in the following sections.

Differences in average returns

Results of formal tests for differences in mean daily returns between the single-commodity portfolio and DBA are presented in Table 2. The estimated differential, defined as the single-commodity portfolio return minus the DBA total return, equals -0.000178. The sign indicates higher average daily performance for DBA, but the difference is not statistically significant.

The conventional t-test yields a p-value of 0.198. Heteroskedasticity-robust inference produces the same conclusion, while the Newey-West HAC specification gives a p-value of 0.204. The 95% stationary-bootstrap confidence interval also contains zero, confirming that the mean daily return differential is not statistically significant.

Table 2. Tests of Mean Return Differences

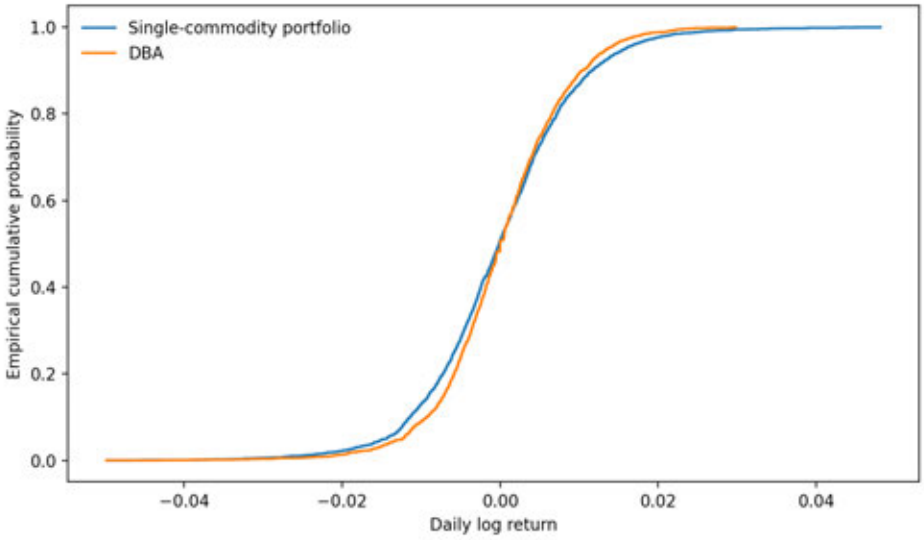
Method	Estimate / statistic	Std. Error	p-value
Conventional t-test	-0.000178	0.000138	0.198
Heteroskedasticity-robust regression	-0.000178	0.000138	0.198
HAC inference (Newey-West, lag = 5)	-0.000178	0.000140	0.204
Wilcoxon signed-rank test	-	-	0.061
Stationary-bootstrap inference	-0.000178	0.000137	0.194
KS distance (descriptive)	D = 0.0577	-	-

Source: Authors' calculations.

The Wilcoxon signed-rank test yields a p-value of 0.061, providing only marginal evidence at the 10% level. Stationary-bootstrap inference likewise confirms that the mean differential is not statistically significant (p = 0.194). Taken together, the daily results provide no robust evidence of a difference in average returns between the two strategies.

The Kolmogorov-Smirnov distance provides complementary descriptive evidence on the overall return distributions. The maximum distance between the two empirical cumulative distribution functions equals D = 0.0577, indicating a modest degree of distributional separation. No conventional KS p-value is reported, because the two contemporaneous strategy returns are not independent samples. The observed distance is consistent with relatively similar central locations combined with differences in dispersion and tail behaviour. Figure 1. plots the empirical cumulative distribution functions and visually illustrates the modest distributional separation summarized by the KS distance.

Figure 1. Empirical Cumulative Distribution Functions of Daily Returns



Source: Authors' calculations.

Note: DBA returns include cash distributions on reinvested total-return basis.

Differences in volatility

The distinction between the two strategies becomes more pronounced once the analysis turns to volatility. As reported in Table 3., the variance of the single-commodity portfolio equals 0.0000961, compared with 0.0000685 for DBA. The variance ratio is 1.402, indicating that daily variance of the single-commodity portfolio is approximately 40.2% higher than that of the distribution-adjusted DBA benchmark.

Statistical evidence strongly supports the descriptive pattern. The classical variance-ratio test rejects equality of variances ($p < 0.001$). The regression-based variance

differential is positive at 0.0000275, and remains highly significant using both heteroskedasticity-robust and Newey-West HAC standard errors. The Newey-West estimate has a standard error of 0.0000049 and $p < 0.001$. Thus, the single-commodity portfolio exhibits significantly higher daily variance than DBA.

Table 3. Volatility Comparison

Measure	Estimate	Std. Error	p-value
Variance (Single-commodity portfolio)	0.0000961	-	-
Variance (DBA total return)	0.0000685	-	-
Variance ratio (Single / DBA)	1.402	-	< 0.001
Variance differential - robust	0.0000275	0.0000034	< 0.001
Variance differential - HAC (NW, lag = 5)	0.0000275	0.0000049	< 0.001

Source: Authors' calculations.

The result is economically meaningful, although it should not be interpreted as a pure diversification effect. DBA combines broader commodity exposure with a different weighting system and futures-contract selection methodology. The evidence therefore shows that the broader DBA structure is associated with lower daily volatility relative to the four-crop portfolio, without isolating the exact contribution of each design feature.

Downside risk: VaR and CVaR

The downside-risk analysis examines whether the volatility difference extends into the lower tail of the daily return distribution. Table 4. reports historical VaR and CVaR at both 95% and 99% confidence levels. The 99% estimates are included to test whether the comparison remains informative deeper in the tail, where the excess kurtosis documented above becomes particularly relevant.

Table 4. Downside Risk Measures (Historical VaR and CVaR)

Measure	Single-Commodity Portfolio	DBA
VaR (95%)	-0.01439	-0.01236
CVaR (95%)	-0.02154	-0.01875
CVaR / VaR (95%)	1.497	1.518
VaR (99%)	-0.02646	-0.02145
CVaR (99%)	-0.03280	-0.02930
CVaR / VaR (99%)	1.239	1.366

Source: Authors' calculations.

At the 95% level, the single-commodity portfolio records a VaR of -0.01439 compared with -0.01236 for DBA. Its CVaR is also more negative (-0.02154 versus -0.01875), indicating a higher loss threshold and a larger average loss within the worst 5% of daily observations. At the 99% level, the VaR difference remains pronounced

(-0.02646 versus -0.02145), while the corresponding CVaR values are -0.03280 and -0.02930. The broader benchmark therefore retains a less adverse absolute downside profile even deep in the left tail.

The CVaR/VaR ratio is higher for DBA at both confidence levels (1.518 versus 1.497 at 95%, and 1.366 versus 1.239 at 99%). This does not imply higher absolute downside risk, because DBA has less negative VaR and CVaR. Rather, once DBA crosses its less adverse VaR threshold, losses deteriorate somewhat more strongly relative to that threshold. The absolute VaR and CVaR levels remain the more direct measures for comparing investor losses across the two strategies.

Overall, the downside-risk evidence is consistent with the daily variance results: the four-crop portfolio is exposed to larger routine and tail losses than DBA. The 99% results nevertheless show that diversification does not remove common extreme agricultural-market risk.

Long-horizon performance

Table 5. summarizes the long-horizon performance measures for the single-commodity portfolio and DBA. The long-horizon comparison provides a different perspective from the daily mean-return tests. With cash distributions reinvested, one dollar invested in the single-commodity portfolio over April 2016 - March 2026 ends at 0.991, corresponding to a cumulative return of -0.88%, and an annualized geometric return of -0.09%. The same initial investment in DBA reaches 1.551, equivalent to a cumulative total return of 55.12%, and an annualized geometric return of 4.49%. DBA also has lower annualized monthly volatility (11.28% versus 12.94%), and a smaller maximum drawdown on the daily wealth path (-41.16% versus -46.76%).

Table 5. Long-Horizon Performance Measures

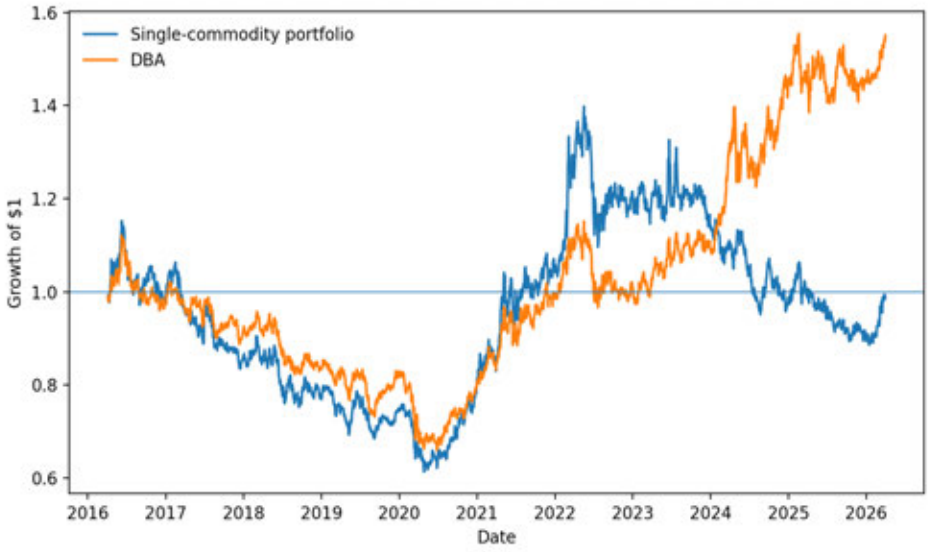
Measure	Single-Commodity Portfolio	DBA
Terminal wealth (initial $1)	0.991	1.551
Cumulative return	-0.88%	55.12%
Annualized geometric return	-0.09%	4.49%
Annualized volatility	12.94%	11.28%
Sharpe ratio	-0.119	0.243
Sortino ratio (MAR = 0)	0.085	0.713
Maximum drawdown (daily wealth path)	-46.76%	-41.16%

Source: Authors' calculations.

Note: DBA is evaluated on a total-return basis with cash distributions reinvested. The Sharpe ratio uses the monthly 3-month U.S. Treasury constant-maturity rate. Sortino ratio uses MAR = 0.

Risk-adjusted measures also favour DBA descriptively. Using the monthly effective 3-month Treasury rate, the Sharpe ratio equals 0.243 for DBA and -0.119 for the single-commodity portfolio, while the respective Sortino ratios are 0.713 and 0.085. However, paired stationary-bootstrap tests do not reject equality of the Sharpe ratios ($p = 0.268$), or the Sortino ratios ($p = 0.247$). The long-horizon evidence therefore demonstrates a sizable realized performance difference over this particular sample, while the statistical evidence on differences in risk-adjusted ratios remains inconclusive. Figure 2. illustrates the corresponding cumulative wealth paths over the sample period.

Figure 2. Growth of $1: Single-Commodity Portfolio and DBA



Source: Authors' calculations.

Note: DBA cash distributions are assumed reinvested.

Monthly-frequency robustness

Repeating the main comparison at monthly frequency produces the same directional pattern but weaker statistical evidence. The complete monthly-frequency results are reported in Table 6. The single-commodity portfolio has an average monthly log return of -0.00007 compared with 0.00366 for DBA, and the Newey-West test of the mean differential is insignificant ($p = 0.149$). Monthly standard deviations are 0.03716 and 0.03239, respectively. The variance ratio is 1.316. The classical F-test is insignificant ($p = 0.136$), while the HAC variance-differential test is marginal at the 10% level ($p = 0.070$). The descriptive KS distance equals $D = 0.1167$, and is reported without a conventional p-value. The Wilcoxon test is also insignificant ($p =$

0.134). With only 120 monthly observations, the lower-frequency analysis naturally has less statistical power than the daily specification.

Table 6. Monthly-Frequency Robustness

Measure	Single-Commodity Portfolio	DBA	p-value / test
Mean monthly log return	-0.00007	0.00366	NW mean diff: 0.149
Monthly standard deviation	0.03716	0.03239	-
Variance ratio (Single / DBA)	1.316	1.000	F-test: 0.136
HAC variance differential	0.000329	-	0.070
KS distance (descriptive)	D = 0.1167	-	-
Wilcoxon signed-rank test	-	-	0.134

Source: Authors' calculations.

Alternative weighting and individual-ETF robustness

The alternative-weighting exercise confirms that the risk comparison is sensitive in magnitude, but not in direction, to portfolio construction. Table 7. reports the results for the three portfolio-weighting schemes. Over the common April 2017 - March 2026 period, variance ratios relative to DBA are 1.382 for equal-weighting, 1.291 for inverse-volatility weighting, and 1.143 for the long-only global minimum-variance portfolio. The Newey-West variance differential remains statistically significant under all three schemes ($p < 0.001$ for equal-weighting and inverse-volatility weighting, $p = 0.009$ for minimum variance). The GMV portfolio nevertheless narrows both the volatility and downside-risk gaps substantially. Thus, optimized allocation among the four crop ETFs can reproduce part, but not all, of the risk reduction observed for DBA.

Table 7. Portfolio-Weighting Robustness, April 2017 - March 2026

Strategy	Daily Std. Dev.	Variance ratio vs. DBA	HAC p-value	VaR (95%)	CVaR (95%)
EW	0.009868	1.382	< 0.001	-0.01440	-0.02181
IVW	0.009535	1.291	< 0.001	-0.01403	-0.02106
GMV	0.008975	1.143	0.009	-0.01371	-0.01993
DBA	0.008394	1.000	-	-0.01246	-0.01901

Source: Authors' calculations.

Note: EW = equal-weighted; IVW = inverse-volatility weighted; GMV = long-only global minimum-variance portfolio. Weights are estimated from the preceding 252 daily observations and rebalanced monthly.

Table 8. presents the individual-ETF comparisons with DBA, and the same conclusion is supported by these comparisons. Each of the four single-commodity ETFs has higher daily volatility than DBA, with variance ratios ranging from

1.694 for SOYB to 4.094 for WEAT. The corresponding Newey-West variance differentials are significant below 0.001 in every case. Their 95% VaR and CVaR values are also more negative than the DBA total-return measures. Thus, the lower risk of DBA is not generated solely by the aggregation of the four crop ETFs into one synthetic portfolio.

Table 8. Individual Single-Commodity ETFs Compared with DBA

ETF	Daily Std. Dev.	Variance ratio vs. DBA	HAC p-value	VaR (95%)	CVaR (95%)
SOYB	0.010773	1.694	< 0.001	-0.01681	-0.02418
WEAT	0.016747	4.094	< 0.001	-0.02421	-0.03448
CANE	0.013728	2.751	< 0.001	-0.02259	-0.02956
CORN	0.012292	2.205	< 0.001	-0.01854	-0.02828
DBA	0.008277	1.000	-	-0.01236	-0.01875

Source: Authors' calculations.

Discussion

The empirical results indicate that the economically relevant distinction between the four-crop portfolio and DBA lies primarily in risk, and realized long-horizon performance rather than in average daily returns. The mean daily return differential between the two strategies is statistically insignificant across the reported tests. At the same time, the cumulative paths show that statistically similar average daily returns do not imply identical long-run wealth outcomes: over the 2016-2026 sample, reinvested distributions and compounding produce materially higher terminal wealth for DBA.

The daily risk evidence is stronger. The single-commodity portfolio has approximately 40% higher variance than DBA, and the difference remains statistically significant under the Newey-West specification. Historical VaR and CVaR also show more adverse downside exposure for the single-commodity portfolio at both, 95% and 99% confidence levels. These results are supported by the individual-fund comparisons: SOYB, WEAT, CANE, and CORN are each more volatile than DBA, and each has more negative 95% tail-risk measures. Broader agricultural exposure is therefore associated with lower sensitivity to shocks affecting individual crop markets in this sample.

The tail results also require qualification. The CVaR/VaR ratio remains higher for DBA, even though its absolute VaR and CVaR are less adverse. Broader exposure therefore lowers the level at which large losses occur but does not eliminate common extreme agricultural-market risk. This interpretation is consistent with the leptokurtic

return distributions observed for both strategies.

The economic interpretation should also distinguish diversification from product design. The four single-commodity ETFs concentrate on corn, soybeans, wheat, and sugar, whereas DBA adds livestock, cocoa, coffee, cotton, and other related exposures. DBA also applies its own commodity weighting and futures-contract roll rules. Consequently, the observed risk difference reflects the combined effect of broader commodity coverage, relative weights, and contract-selection methodology rather than a pure diversification effect that can be isolated from ETF structure. This interpretation is consistent with the commodity literature emphasizing the importance of term structure, rebalancing, and allocation design (Erb, Harvey, 2006; Bessler, Wolff, 2015).

The robustness analysis further qualifies the central result. Equal-weighted, inverse-volatility, and minimum-variance portfolios all remain more volatile than DBA over the common robustness period, although the minimum-variance allocation narrows the gap considerably. Monthly-frequency tests preserve the direction of the mean and volatility differences. The monthly variance differential is only marginal at the 10% level, because the sample contains 120 observations. Sharpe and Sortino ratios are higher for DBA, but paired stationary-bootstrap tests do not establish statistically significant differences. These findings support a cautious conclusion: DBA provides a more resilient realized risk profile in the sample, while the magnitude of its advantage depends on portfolio weighting and the measurement horizon.

Several limitations remain. The empirical sample consists of four Teucrium single-commodity ETFs and one diversified benchmark from another issuer, so the results should not be generalized to the entire agricultural ETF universe. DBA retains partial exposure to the same crop markets and differs in roll methodology, which prevents a clean causal decomposition of diversification and product-design effects. Cash distributions are incorporated on a reinvested, pre-tax basis, while transaction costs generated by synthetic monthly rebalancing are not deducted. Although monthly rather than daily rebalancing reduces the practical importance of trading costs, both assumptions should be considered when interpreting realized wealth comparisons. Future research could broaden the sample, where sufficiently long histories become available and examine whether the results vary systematically across market regimes.

Conclusion

This paper examined whether a portfolio of single-commodity agricultural ETFs differs from a broader agricultural ETF benchmark in terms of return and risk characteristics. The analysis constructs a monthly-rebalanced portfolio of

SOYB, WEAT, CANE, and CORN, and compares it with DBA over April 2016 - March 2026.

The main findings can be summarized as follows. First, using DBA total returns that incorporate reinvested cash distributions, there is no statistically significant difference in average daily returns between the single-commodity portfolio and DBA. Second, the single-commodity portfolio exhibits significantly higher daily variance, and more adverse 95% and 99% downside-risk measures. Third, with DBA cash distributions reinvested, the benchmark generates substantially higher terminal wealth and annualized realized return, and a smaller maximum drawdown over the full sample. Its Sharpe and Sortino ratios are also higher, although paired stationary-bootstrap tests do not establish statistically significant differences in these risk-adjusted measures.

The weighting robustness results add an important qualification. The volatility and downside-risk gaps remain under equal, inverse-volatility, and long-only minimum-variance weighting. Minimum-variance allocation substantially narrows the difference, but the variance differential remains statistically significant. Broader commodity exposure is therefore associated with a more resilient risk profile in the baseline comparison, while risk-sensitive allocation among the four crop ETFs can replicate part of that advantage.

The findings should be interpreted within the limits of the sample and fund structures examined. DBA is a single diversified benchmark and remains partially exposed to the same crop markets as the single-commodity portfolio. It also differs in contract-selection and roll methodology. The analysis assumes reinvestment of DBA cash distributions without taxes, and does not deduct transaction costs from the synthetic monthly rebalancing. These features, together with the limited number of funds, restrict the extent to which the estimated differences can be attributed exclusively to diversification, or generalized beyond the sample.

Overall, the evidence indicates that the broader DBA structure provided lower daily volatility and downside risk than the baseline portfolio of four single-commodity agricultural ETFs during 2016-2026. The daily mean-return difference is not statistically significant, while the long-horizon results reveal economically meaningful differences in compounded wealth, when DBA cash distributions are reinvested. The minimum-variance robustness exercise shows that portfolio construction materially influences the size, but not the direction, of the risk advantage. Accordingly, the results support broader agricultural exposure as a potentially more resilient investment structure within the sample, rather than establishing a universal dominance of diversified agricultural ETFs.

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