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Liquidity Components and Informational Efficiency in the US Agricultural Futures Markets

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Abstract

The objective of this work is to assess the relationship between informational efficiency and liquidity in the US agricultural futures markets. To this end, it employs daily data from January 2018 to February 2025, the Generalized Spectral approach for testing the martingale difference hypothesis, and statistics suitable for analyzing complex (non-linear and non-monotonic) associations. According to the empirical results, the US agricultural futures markets have been largely efficient. The COVID-19 pandemic and the war in Ukraine had a negative (although short-lived) impact on the performance certain markets. The informational efficiency appeared to maintain a positive (negative) relationship with the permanent (temporary) component of market liquidity. There is some evidence of informational efficiency synchronization.

JEL Classification: G14, Q13, C22
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1. Introduction

The futures markets provide hedging instruments, facilitate price discovery, and offer commodities as an alternative asset class to investors for portfolio diversification. Therefore, their functioning/performance is of paramount importance for commercial traders, hedgers, speculators, policy-makers, regulatory bodies, and research economists. In Economics and Finance, the functioning of a market is linked to the degree to which prices reflect the available information. The efficient market hypothesis (EMH) (Fama, 1970) posits that markets are informationally efficient in the sense that, by the actions of rational traders, prices instantly and accurately reflect all information relevant to fundamental values. Fama (1991) distinguished between weak-, semi-, and strong-form efficiency depending on whether the information set contains historical prices only, historical prices and public information, and historical prices, public and private information, respectively.

The economic implication of the weak-form informational efficiency (which is the most relevant for empirical work) is that prices are unpredictable and no trader can make consistently over time abnormal price returns (i.e., in excess of average market price returns adjusted to risk) by exploiting past price information. Because the best forecast of tomorrow's return in an informationally efficient market is today's return, the EMH has been connected to the random walk (RW) theory. Campbell *et al*. (1998) noted that, depending on the properties of the return distribution, there are three types of RW sequences: (a) the RW1, involving independent and identically distributed returns; the RW2, with independent but not identically distributed returns (or alternatively, mean-independent returns); and the RW3, with uncorrelated returns. The RW2 implies that price returns are martingale sequences (MS) (Samuelson, 1965).

The empirical literature on the informational efficiency of commodity futures markets is large. What follows is a list of representative works. MacDonald and Taylor (1988), Yu *et al*. (2006), Lee and Lee (2009), and Pathak *et al*. (2020) investigated futures markets for metals; Escanciano and Velasco (2006) and Lazar *et al.* (2012) futures markets for currencies; Tabak and Cajuero (2007), Aslam *et al*. (2022) and Charles and Darne (2009) futures markets for energy; Kaur and Rao (2010) futures markets for agricultural commodities; Kristufek and Vosvrda (2014), Chakraborty and Das (2015), Bohl *et al*. (2021), and Adu and Idakwoji (2024) panels of futures markets involving agricultural, energy, and metals; and Kristufek (2018), Mokni *et al*. (2024) and Karasinski (2025) cryptocurrency markets.

The investigations relied on a variety of statistical/econometric tools including stationarity tests (ADF, KPSS, and Variance Ratio (VR)) (MacDonald and Taylor, 1988; Yu *et al*., 2006; Charles and Darne, 2009; Lee and Lee, 2009), Autocorrelation and Runs tests (Kaur and Rao, 2010; Mokni *et al*., 2024), Rescaled Range and Fractal Analysis (Tabak and Cajuero, 2007; Kristufek and Vosvrda, 2014), Entropy (Chakraborty and Das, 2015; Kristufek, 2018), Detrended Fluctuation Analysis (Aslam *et al*., 2022; Bui *et al*., 2025), Automatic Variance Ratio (AVR) tests (Bohl *et al*., 2021; Adu and Idakwoji, 2024), and Generalized Spectral tests (GS) (Escanciano and Velasco, 2006; Lazar *et al*., 2012; Pathak *et al*., 2020).

The findings are generally conflicting and appear to depend on the markets considered, the quantitative tools employed, and whether the analysis has been static (full sample) or dynamic (through rolling windows). The dependence on the adopted approach is natural given that different tools are based on different assumptions. For example, the standard stationary tests assume that the underlying stochastic process is RW1 whereas the AVR and the GS tests that it is RW2; also, while the AVR test and the Rescaled Range Analysis assume linearity, the GS test does not. The dependence on the type of analysis (static vs dynamic) is consistent with the Adaptive Market Hypothesis (AMH) (Lo, 2004) according to which information efficiency is not an all-or-none proposition but a market characteristic evolving in a constantly changing economic environment and under complex interactions among agents who possess bounded rationality.

The existence or lack of predictability of current returns from past returns is a feature of the price formation process. During the last 20 years, it has been widely recognized that, over short time intervals, the microstructure (i.e., the attributes) of financial markets may have a more important role in shaping asset price dynamics relative to macroeconomic variables (e.g., O'Hara, 2003; Chordia *et al*., 2008; Patra and Hiremath, 2024). Chordia *et al*. (2008) illuminated the potential relevance of market liquidity. In particular, they put forward two competing hypotheses: (a) Market makers (such as day and floor trades and floor brokers trading on their own account) have no cognitive limitations to detect deviations between quotes and fundamental (full-information) values. Then, their proclivity to submit arbitrage trades will be positively related to liquidity (implying, thus, that return predictability decreases with market liquidity). (b) Market makers have cognitive limitations and misinterpret the information content of order flows. The mispricing will provide incentives to outside agents to collect information and trade on it. The arbitrage activity of outside agents will improve efficiency but, at the same time, it will increase the adverse selection of market makers (implying that return predictability decreases with market illiquidity).

The number of empirical works on the association between informational efficiency and liquidity is small. The relevant empirical findings are mixed and, at the same time, difficult to compare, as different authors very often employ different liquidity measures (proxies). Chordia *et al*. (2008), Smith (2008), Chung and Hrazdil (2010), and Bariviera (2011) focused on stock markets. Chordia *et al*. (2008) and Chung and Hrazdil (2010) employed the bid-ask spread as a liquidity proxy and concluded that increased liquidity enhances market efficiency. A positive relation was also reported by Smith (2008) who used the market capitalization, the number of stocks, and the turnover ratio as liquidity proxies. Bariviera (2011), however, found a weak (and under certain model specifications) negative association between efficiency and liquidity (measured by market capitalization and foreign trading).

Turning to empirical works on commodities, Bohl *et al*. (2021) using the Amihud measure found that illiquidity had no impact on informational efficiency; Patra and Hiremath (2024), using the Amihud measure, the trading volume, the high-low price spread, and the turnover ratio as proxies reported time-varying relationships involving periods of a positive and negative association; and Mokni *et al*. (2024) reported a negative association between informational efficiency and liquidity (proxied by the trading volume divided by market capitalization).

In this context, the objective of the present work is to investigate the association between informational efficiency and liquidity in the US agricultural futures markets. To this end, it relies on daily (January 2018 to February 2025) information from ten markets, the Generalized Spectral (GS) test by Escanciano and Velasco (2006), and two liquidity measures, namely, the Amihud (2002) index and the Microstructure Noise index (Jain *et al*., 2024).

The GS is probably the most powerful test for investigating the null that price returns are martingale sequences. It detects a wide range of linear and non-linear dependencies in the conditional mean; it is robust against conditional heteroscedasticity; it dispenses with the need to formulate a parametric alternative or to smooth the data; it considers dependence at all lags (no need to select the lag order); and it has good asymptotic properties (e.g., Escanciano and Velasco, 2006; Charles *et al*., 2011; Lazar *et al*., 2012).

Among the illiquidity measures, the Amihud (2002) index has the maximal correction ratio. Therefore, it is strongly recommended for empirical research (e.g., Marshall *et al*., 2012; Zhang and Ding, 2021). The Microstructure Noise index has been recently proposed by Jain *et al*. (2024); it captures the transitory component of liquidity (i.e., the one associated with changes occurring within a trading day) while the Amihud index reflects the permanent component of it.

The contributions of the manuscript to the literature are:

(a) To the best of our knowledge, this is the first work which assesses informational efficiency in agricultural commodities futures with the GS test.

(b) It considers the association between informational efficiency and two different components of market liquidity. This is important since it allows us, for the first time, to investigate whether permanent and transitory liquidity have the same impact on informational efficiency.

(c) It employs statistics suitable for analyzing complex (non-linear and non-monotonic) links. Given that the pattern of association between efficiency and liquidity is not a priori known, the use of flexible statistics enhances the robustness of the empirical findings.

(d) It relies on both static (full-sample) and dynamic analysis. The latter appears to be necessary not only because informational efficiency (and its association with liquidity) may be time-varying but also because the period under consideration involves two major crises (namely, the COVID-19 pandemic and the war in Ukraine) that have affected agricultural commodities markets through multiple channels. Economic turmoil may trigger traders' overreaction to news and herding behavior with a detrimental impact on informational efficiency (e.g., Gleason et al., 2004; Aslam et al., 2020). Aslam et al. (2020) and Aslam et al. (2022) reported a decline in the informational efficiency of FOREX and energy markets during the initial phase of the COVID-19 pandemic and the war in Ukraine, respectively. Adu et al. (2024), however, found that the war in Ukraine had little or no effect on the informational efficiency in a panel of commodity futures (agricultural, energy, and metals) markets

In what follows, section 2 discusses the methodology (analytical framework); section 3 presents the data and the empirical models, and section 4 the empirical results. Section 5 offers conclusions.

2. Analytical framework

2.1 The generalized spectral test for the martingale difference hypothesis

Let r_t $(t = 1, 2, \dots, T)$ be the returns (logarithmic increments) of an asset's

price. Given an unconditional expectation of r_t equal to μ, the null hypothesis that r_t is a martingale sequence is

$$H_o: E(r_t / r_{t-1}, r_{t-2}, \dots) = 0 \qquad (1),$$

almost surely (a.s.) The GS test adopts a pair-wise approach by taking into account the dependencies at all lags in the sample. Therefore, the null hypothesis (1) may be expressed as

$H_0: m_j(r) = 0 \;\; \forall j \geq 1 \qquad (2)$

a.s., where $m_j = E(r_t - \mu / r_{t-j} = r)$ are pair-wise regression functions. The alternative hypothesis is

$$H_A: \text{there exists } j \geq 1, \qquad \text{such that } P(m_j(r) \neq 0) > 0 \qquad (3).$$

Following Bierens (1982), (3) may be reformulated as

$$H_0: \gamma_j(x) = 0 \quad \forall j \geq 1 \qquad (4),$$

where $\gamma_j(x)$ is a measure of conditional mean dependence (a generalization of the usual autocovariances) in a non-linear time series framework. The generalized spectral distribution function of r_t, $H(\lambda, x) = \gamma_0(x)\lambda + 2\sum_{j=1}^{\infty} \gamma_j(x)(\frac{\mathrm{sinj}\pi\lambda}{j\pi})$ with $\lambda \in [0, 1]$ becomes, under the null hypothesis, $H_0(\lambda, x) = \gamma_0(x)\lambda$. Escanciano and Velasco (2006) by: (a) forming the differences between the sample estimates of the two functions $\widehat{S_T}((\lambda, x) = \widehat{H}(\lambda, x) - \widehat{\gamma_0}(x)\lambda$; (b) measuring the distance of $\widehat{S_T}(\lambda, x)$ to zero for all possible values of x and λ using the Cramer-von Mises norm; and (c) employing the cumulative distribution of the standard normal as a weighting function, arrived at the following test statistic:

$$D_T^2 = \sum_{j=1}^{T-1} \frac{T-j}{(j\pi)^2} \sum_{t=j+1}^{T} \sum_{s=j+1}^{T} (r_t - \bar{r}_{T-j})(r_s - \bar{r}_{T-j}) \exp\left[-0.5(r_{t-j} - r_{s-j})^2\right] \quad (5).$$

The asymptotic null distribution of (5) depends on the data generation process (DGP). *p*-values robust against higher order dependence (including conditional heteroscedasticity) are calculated using wild bootstrap.

2.2 Illiquidity indices

For commodities futures, the Amihud illiquidity index is defined as

$$AM_t = \frac{|r_t|}{V_t} \quad (6),$$

where V_t is volume (measured in the number of contracts traded at *t*). Higher values of the AM point to a larger degree of price sensitivity to volume and, thus, to a less liquid market. Jain *et al*. (2022) note that the AM reflects changes in the fundamental or intrinsic values (i.e., it captures the permanent component of commodities futures liquidity); as such, it is of interest to long-run speculators and commercial traders. The Microstructure Noise index, in contrast, captures the transitory component by focusing on changes within a trading date; it is important for frequent intraday traders (Goettler *et al*., 2009). The microstructure noise is defined as

$$MN_t = \frac{(H_t - L_t) - |C_t - O_t|}{C_t} \quad (7),$$

where H_t, L_t,C_t, and O_t are the high, the low, the closing, and the opening price at *t* (Jain *et al*., 2024). Liquid contracts easily absorb supply and demand imbalances resulting in smaller differences between H_t and L_t. To purge the influence of news affecting the intrinsic prices but is unrelated to microstructure noise, one has to subtract the absolute difference between closing and opening prices. Finally, the normalization with the closing price ensures that the MN index is unitless and comparable across commodities (Jain *et al*., 2024).

3. The data and the empirical models

The data for the empirical analysis is daily prices and volumes from ten agricultural commodities futures markets in the US. It has been obtained from Yahoo Finance and covers the period 01/01/2018 to 28/02/2025. Seven of the commodities are grains (Corn, Soybeans, Soybean Meal, Soybean Oil, Soft Wheat, Hard Wheat, and Oats) and three are livestock (Feeder Cattle, Live Cattle, and Lean Hogs).

Figure A.1 in the Appendix presents the evolution of the respective logarithmic prices. The prices of all 7 grains exhibited an upward trend from 2020 to 2022 followed by a downward trend afterwards. The prices of Feeder Cattle and Live Cattle increased steadily since 2020 whereas that of Lean Hogs increased until 2022 and showed a tendency to stabilize afterwards.

Table A.1 in the Appendix presents descriptive statistics and tests on the distribution of price returns. All distributions are leptokurtic (suggesting a greater chance of occurrence of extreme positive and negative returns relative to the normal distribution). Eight distributions (Corn, Soybeans, Soybean Meal, Soybean Oil, Soft Wheat, Oats, Live Cattle and Lean Hogs) exhibit negative skewness (meaning that their respective tails are more pronounced to the left than the right), one distribution (Feeder Cattle) exhibits positive skewness while that of Hard Wheat is symmetric. As is typically the case with financial data, the null of normality is strongly rejected for all return sequences.

Table A.2 in the Appendix shows descriptive statistics for the two illiquidity indices. Because of the vast differences in the number of contracts traded, it is meaningless to compare the AM values across markets. From the MN values, however, it appears that Oats has the highest (0.014) transitory illiquidity component and Live Cattle has the lowest (0.005) one.

The Generalized Spectral tests have been conducted using the R package "*vrtest*" (Kim, 2023). The rolling window length for the dynamic analysis has been set equal to 125 trading days (1/2 years, approximately) to obtain more detailed information. In the relevant literature (e.g. Lazar *et al*., 2012; Pathak *et al*., 2020; Bohl, *et al*., 2021; Mokni *et al*., 2024), window lengths from 100 to 500 trading days have been employed. Here, initial experimentation indicated that the empirical findings from the selected window length are qualitatively very similar to those from a length of 250 trading days. This, in turn, is consistent with the evidence in Pathak *et al*. (2020) and Bohl *et al*. (2021). Rolling windows of the 125 trading days length have also been applied to compute the sub-period means of the AM and the MN sequences.

To investigate the relationship between liquidity and informational efficiency, the present work relies on three measures of association, namely, the Pearson *rho*, the Spearman *rho*, and the Maximal Information Coefficient (MIC). The first two are signed and capture the strength of a relationship under the assumption of linearity and monotonicity, respectively. The MIC is unsigned and captures the intensity of a wide range of associations both functional and not; its value ranges between 0 for independent sequences and 1 for a noiseless functional relationship (Reshef *et al*., 2011). Dependence is a more general notion than correlation as two sequences can be uncorrelated but still dependent. The MIC comes together with two other maximal information-based non-parametric exploration (MINE) statistics, namely, the difference between the MIC and the squared Pearson *rho* (MIC-ρ^2) and the Maximal Asymmetry Score (MAS). Large values of the former (latter) statistic are consistent with non-linearity (non-monotonicity) (Reshef *et al*., 2011). The three MINE statistics provide rich insights into associations of interest and, at the same time, they allow one to evaluate the validity of evidence obtained from standard measures such as the Pearson and Spearman correlation coefficients. Here, given the arguments by Chordia *et al*. (2008) that the sign of the association between efficiency and liquidity depends on the type of agents submitting arbitrage trades (market makers vs outside traders) there is no a priori reason whatsoever to expect linear or monotonic relationships.

4. The empirical results

Table 1 presents the GS test results from the full-sample analysis. The *p*-value is smaller than the conventional levels of significance only for the Soybean Oil and the Lean Hogs futures markets; for the remaining eight commodities the null hypothesis that price returns are martingale sequences is not rejected. The markets of Soft Wheat, Corn, and Hard Wheat (in this order) performed much better than the rest. Kristoufek and Vosvrda (2014), using a composite efficiency index and data from 2000 to 2013, reported that the futures markets of grains were more efficient than those of livestock. Bohl *et al*. (2021), using the AVR test and data from 1992 to 2017 found that the futures markets of Soybeans and Corn exhibited the lowest levels of predictability whereas those of Hard Wheat and Feeder Cattle the highest.

Figure 1 shows the results of the dynamic analysis[1]. In line with what has been already transpired from Table 1, violation of the martingale property is (even at the 10 per cent level of significance) the exception rather than the rule. The visual evidence is corroborated by the absolute and relative inefficiency scores in Table 2. For Soybean Oil (the worst performer in the full-sample analysis), informational efficiency is rejected in 4.43 per cent of windows at the 5 per cent level and in 6.67 per cent of windows at the 5 to 10 per cent level. In contrast, for Soft Wheat (the best performer in the full-sample analysis) informational efficiency is rejected in 0.8 per cent of windows at the 5 per cent level and in 1.97 per cent of windows at the 5 to 10 per cent level. Therefore, although the *p*-values from the GS test vary widely over the rolling windows, the evidence in favor of the Adaptive Market Hypothesis (Lo, 2004) is rather weak; the agricultural future markets in the US had, generally, exhibited a sustained market efficiency.

The visual inspection of Figure 1 suggests that, in the majority of markets, (most notably for Soybeans, Soybean Meal, Soybean Oil, and Oats) a sizable part of martingale property rejections occurred in windows ending in late 2020 (or given the window length, in sub-periods beginning in early 2020). In addition, for certain markets (Corn, Soybean Oil, Hard Wheat, and Oats) a sizable part of martingale property rejections occurred in sub-periods beginning in early 2022. There is, therefore, evidence that the COVID-19 pandemic and the war in Ukraine had (at least during their respective initial phases) a negative impact on informational efficiency. In this sense, the findings here are consistent with those reported by Aslam *et al*. (2020) and Aslam *et al*. (2022) for the FOREX and energy markets, respectively.

The term efficiency synchronization refers to the presence of a common trend in informational efficiency across different markets (Bohl *et al*., 2021; Pathak *et al*., 2020). The visual evidence from Figure 1 has already indicated that, over certain sub-sub-periods (e.g. during the initial phases of the COVID-19 pandemic and the war in Ukraine), the *p*-values from the GS test in several markets moved in tandem. To substantiate it further (and following Bohl *et al*., 2021), Table 3 presents pairwise Spearman correlation coefficients for changes in the *p*-values (i.e., changes in the probability of not rejecting the null hypothesis) from the GS test[2]. Seventeen out of forty-five coefficients are statistically significant at the conventional levels. From these, only one (for the pair Soybean Meal and Oats) is negative. There is, therefore, evidence of efficiency synchronization for a part of the markets considered. Bohl *et al*. (2021) reported that common trends in efficiency were generally absent either between commodity groups (e.g., agricultural and metals) or between individual commodities in the same group. It is noteworthy that most of the strongest associations here involve markets that are either linked vertically in a given physical supply chain (the pairs (Soybeans, Soybean Meal), (Soybeans, Soybean Oil), (Feeder Cattle, Live Cattle)) or they correspond to varieties (classes) of the same underlying physical commodity (the pair (Soft Wheat, Hard Wheat)).

From the visual inspection of Figure 1, one can hardly detect a systematic co-movement between the *p*-values from the GS test and any of the two illiquidity indices. There are sub-periods in which low *p*-values are associated with high AM or/and MN values (pointing to a negative relationship between informational efficiency and liquidity) and sub-periods in which low *p*-values are associated with low AM or/and MN values (suggesting a positive

[1] Because the magnitudes of the two illiquidity indices are generally very small relative to the *p*-values from the GS test the rolled AM and MN series have been, for the construction of Figure 1, multiplied ("inflated") by appropriate constants to facilitate visual comparison of the evolution of all three series. This, naturally, has no impact whatsoever on the empirical findings.

[2] The use of changes (first differences) is necessary since the individual *p*-values series (as expected due to the application of rolling windows analysis) exhibit strong serial correlation.

relationship). The association between efficiency and the two liquidity components is time-varying.

Table 4 shows the Pearson and Spearman correlation coefficients between changes in *p*-values from the GS test and changes (first differences) in the two illiquidity measures. For the AM index, three Pearson and six Spearman correlation coefficients are statistically significant at the conventional levels and all have a negative sign. For the MN index, five Pearson and four Spearman correlation coefficients are statistically significant at the conventional levels and they all have a positive sign.

Table 5 presents the MINE statistics on the association between changes in the *p*-values from the GS test and changes in the two illiquidity measures. All MIC statistics are strongly statistically significant and larger (in absolute value terms) than the corresponding Pearson and Spearman measures. The statistical significance of the MIC measures suggests that, for all markets, informational efficiency and liquidity are dependent sequences. Given that dependence is a more fundamental notion than correlation, the finding implies that the preoccupation of research economists with the link between the two variables is well justified. Based on the MIC-ρ^2 statistic, the linearity of the association between the *p*-values and the AM measure is rejected everywhere; the same is true (at the 10 per cent level or less) in nine out of ten cases for the MN measure. Based on the MAS statistic, the monotonicity of the association is rejected (at the 10 per cent level or less) in seven cases for the AM and in just two cases for the MN.

Taking the evidence from Tables 4 and 5 together one with a high degree of confidence, due to the statistical significance of Spearman correlation coefficients and the consistency of the monotonicity assumption with the data, may conclude that for five (Soft Wheat, Hard Wheat, Oats, Feeder Cattle, and Live Cattle) out of ten markets there is a monotonic (positive) relationship between informational efficiency and the MN illiquidity index. For each of the remaining five markets, one can only infer (from the MIC statistic) that there exists either a non-linear or a non-linear and non-monotonic relationship, the sign of which cannot be determined from the information provided by the tests[3].

Things are somehow more complicated with the AM illiquidity index. Although Spearman's correlation is negative in six markets (Soybean Oil, Soft Wheat, Hard Wheat, Feeder Cattle, Live Cattle, and Lean Hogs), the corresponding MAS measure is (at the 10 per cent level or less) statistically significant in five of them (Soybean Oil, Soft Wheat, Hard Wheat, Live Cattle, and Lean Hogs); implying that monotonicity is probably restrictive for describing the association between return predictability and the AM. For each of the remaining four markets, all one can infer (from the MIC statistic again) is that there exists a non-linear and non-monotonic relationship, between informational efficiency and the AM index, the sign of which cannot be determined from the information provided by the tests.

[3] A non-monotonic relationship implies that there are combinations of efficiency and liquidity where their association is positive and combinations where their association is negative. This is certainly in line with the theoretical arguments of Chordia *et al*. (2008).

5. Conclusions

The objective of the present work has been to investigate the relationship between informational efficiency and liquidity in the US agricultural futures markets. This has been pursued using the Generalized Spectral test (a powerful statistical tool for testing departures from the martingale difference property); two complementary market liquidity measures (the Amihud and the Microstructure Noise index capturing the permanent and the transitory liquidity market components, respectively), and a number of non-parametric statistics suitable for assessing the strength and the salient characteristics of potentially complex associations.

The empirical results suggest:

(a) During the period of analysis, the ten agricultural futures markets considered exhibited (generally) sustained informational efficiency. Violations of the martingale property for returns were sporadic; the relative inefficiency scores for the large majority of the markets remained well below 10 per cent. There was little scope for public regulatory interference as price return predictability was low. The markets, therefore, were suitable for risk-averse investors who traded for normal profit and employed portfolio rebalancing for diversification. Efficiency, even during crises, is an indication of resiliency. It appears, therefore, that public regulators should keep potential inventions in these markets to the minimum possible extent.

(b) The effects of the COVID-19 pandemic and the war in Ukraine were market-specific (certain markets- but not all- experienced a deterioration in their informational efficiency during the initial phases of these two major crises). Nevertheless, these effects were short-lived.

(c) There was informational efficiency synchronization especially between markets that are linked vertically in a physical supply chain or involve varieties of the same underlying physical commodity.

(d) In all markets, liquidity and return predictability were dependent sequences. Their relationship was typically a complex one and, thus, difficult to capture through standard measures of correlation. This is probably the reason behind the mixed, weak, and inconclusive findings reported in the majority of the earlier empirical works on the topic.

(e) The permanent component of liquidity maintained, in most markets, a negative association with return predictability whereas the opposite was the case with the temporary component of it.

Chordia *et al*. (2008) attributed the positive relationship between informational efficiency and liquidity to arbitrage trading from market makers and the negative to arbitrage trading from outside agents. The findings of the present work can be explained within the framework proposed by Chordia *et al*. (2008), provided that the permanent (temporary) market liquidity component is associated with actions of market makers (outside) agents. Nevertheless, it should be emphasized that the narrative by Chordia et al. (2008) was a reference to a hypothetical behavioral channel that has not yet been directly tested. Therefore, further theoretical and empirical work is necessary to empirically distinguish the roles of different agents in the link between efficiency and liquidity.

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Appendix

Figure 1. Rolling windows results. *p*-value, AM and MN
(The dashed lines represent the 0.05 and 0.1 *p*-value thresholds)

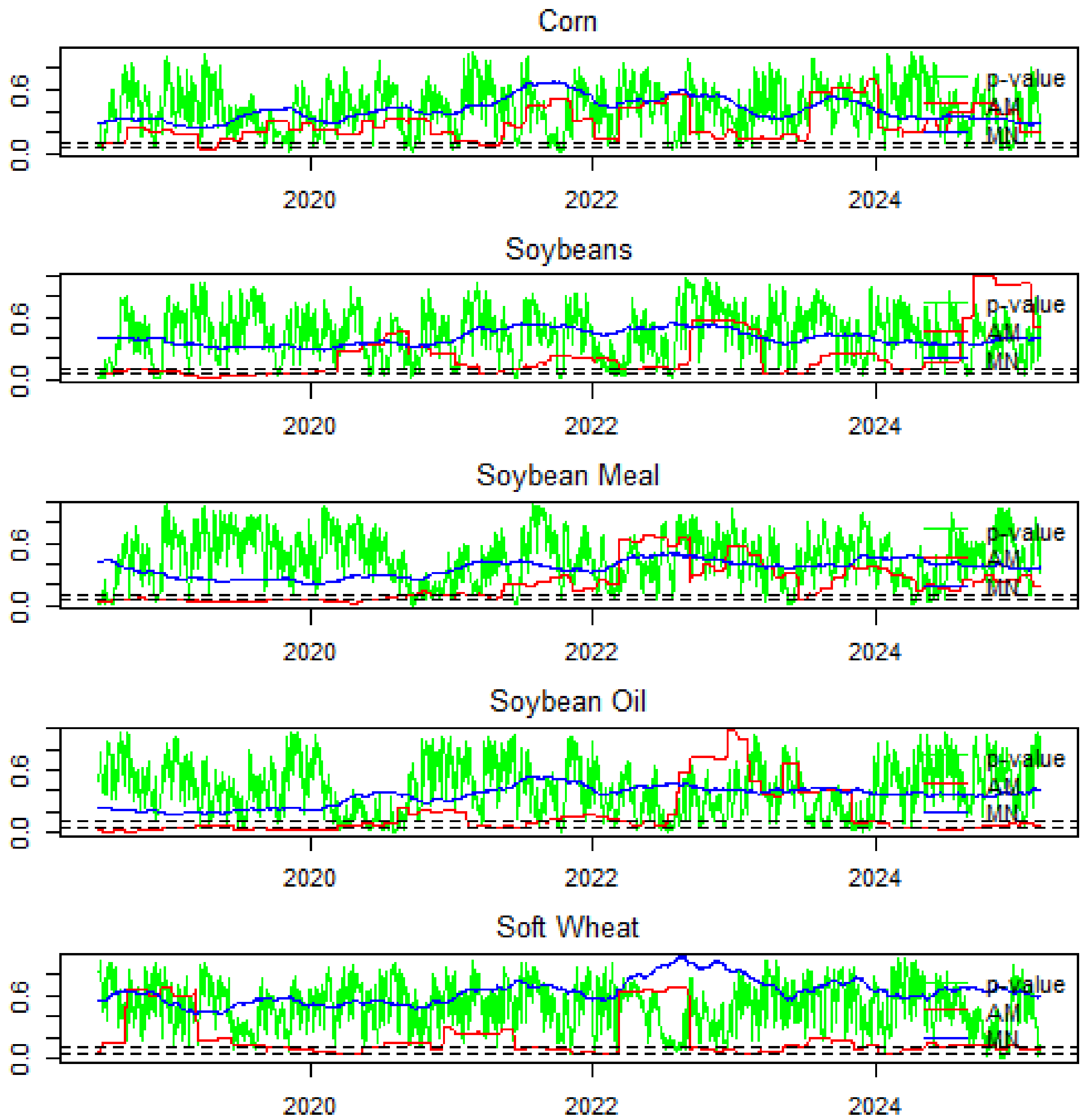

Figure 1 (continued). Rolling windows results. *p*-value, AM and MN
(The dashed lines represent the 0.05 and 0.1 *p*-value thresholds)

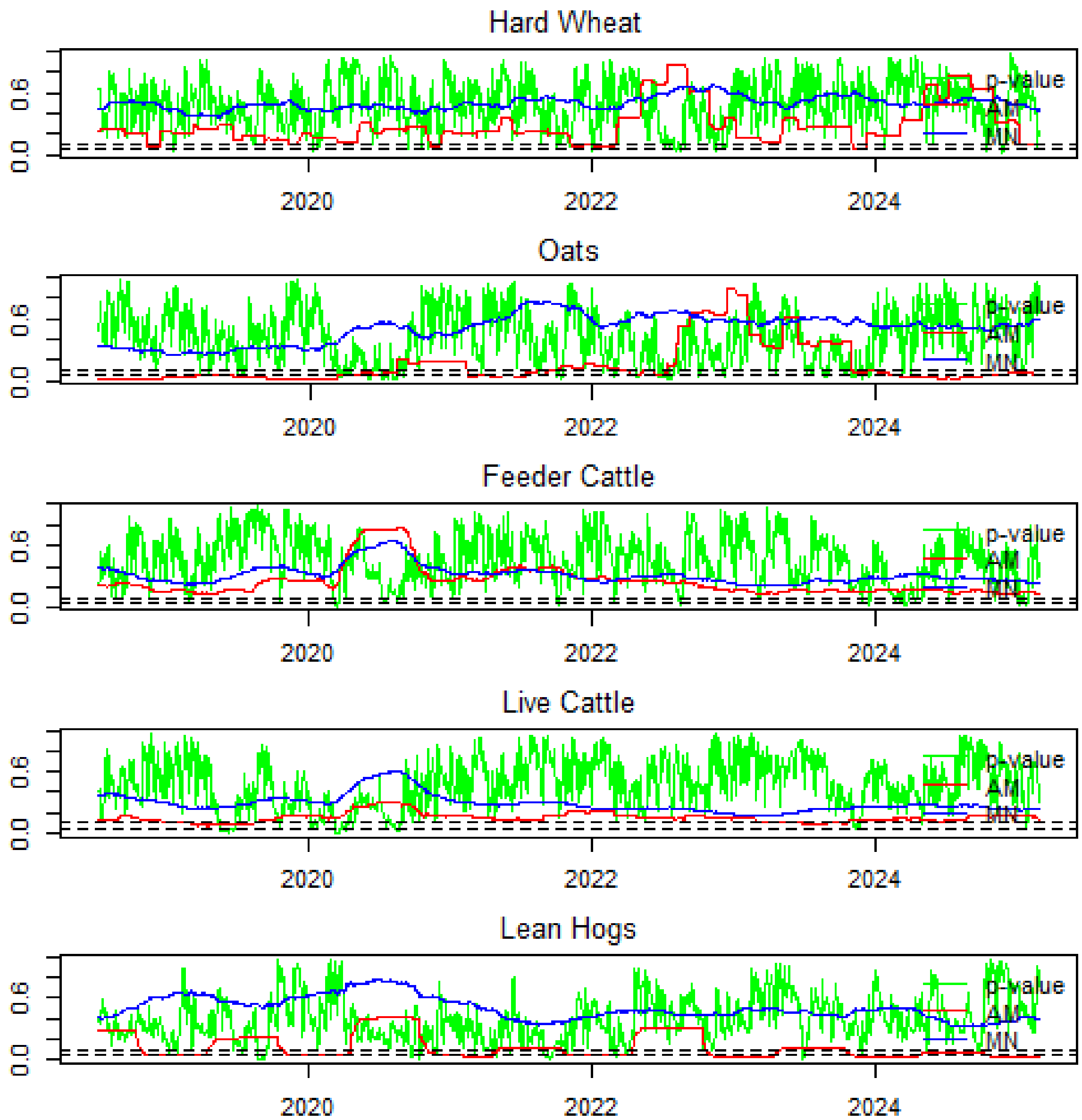

Table 1. Generalized spectral test results. Full-sample (static) analysis.

Commodity	*p*-value	Commodity	*p*-value
Corn	0.837	Hard Wheat	0.731
Soybeans	0.516	Oats	0.363
Soybean Meal	0.226	Feeder Cattle	0.292
Soybean Oil	0.021	Live Cattle	0.422
Soft Wheat	0.858	Lean Hogs	0.031
Note: The *p*-values are based on 1000 Wild Bootstrap replications.			

Table 2. Absolute and relative inefficiency

	p-value $\leq$ 0.05		p-value $\in$ (0.05, 0.10]	
	Number of windows	% of windows	Number of windows	% of windows
Corn	36	2.15	80	4.79
Soybeans	68	4.06	95	5.68
Soybean Meal	63	3.82	54	3.21
Soybean Oil	74	4.43	113	6.67
Soft Wheat	13	0.8	33	1.97
Hard Wheat	16	0.96	45	2.71
Oats	35	2.19	86	5.4
Feeder Cattle	29	1.74	66	3.95
Live Cattle	56	3.42	53	3.19
Lean Hogs	46	2.75	56	3.4

Table 3. Pairwise Spearman correlation coefficients

(changes in *p*-values from the GS test)

	Corn	Soybeans	Soybean Meal	Soybean Oil	Soft Wheat	Hard Wheat	Oats	Feeder Cattle	Live Cattle	Lean Hogs
Corn										
Soybeans	0.166 (<0.01)									
Soybean Meal	0.097 (<0.01**)**	0.304 (<0.01)								
Soybean Oil	0.076 (<0.01)	0.163 (<0.01)	0.02 (0.424)							
Soft Wheat	0.171 (<0.01)	0.079 (<0.01)	0.067 (<0.01)	-0.019 (0.453)						
Hard Wheat	0.08 (<0.01)	0.064 (0.011)	0.064 (0.012)	0.011 (0.649)	0.326 (<0.01**)**					
Oats	0.013 (0.615)	-0.007 (0.779)	-0.09 (<0.01)	-0.035 (0.169)	0.016 (0.537)	-0.004 (0.886)				
Feeder Cattle	0.104 (<0.01)	0.016 (0.523)	-0.017 (0.494)	0.024 (0.339)	0.038 (0.133)	0.044 (0.083)	0.037 (0.145)			
Live Cattle	-0.007 (0.786)	-0.005 (0.827)	-0.006 (0.797)	-0.041 (0.103)	0.009 (0.709)	0.037 (0.139)	0.006 (0.798)	0.184 (<0.01)		
Lean Hogs	0.011 (0.657)	-0.039 (0.118)	-0.037 (0.144)	0.01 (0.689)	-0.007 (0.77)	-0.019 (0.443)	-0.029 (0.241)	0.033 (0.188)	0.031 (0.224)	

Note: *p*-values in parentheses; obtained using Block Bootstrap with 1000 replications

Table 4. Pearson and Spearman correlation

(changes in the *p*-values from the GS test and in illiquidity measures for the same market)

	AM		MN	
	Pearson	Spearman	Pearson	Spearman
Corn	0.03 (0.213)	-0.042 (0.087)	0.032 (0.186)	-0.013 (0.558)
Soybeans	0.012 (0.601)	-0.01 (0.679)	0.026 (0.287)	0.037 (0.123)
Soybean Meal	0.038 (0.124)	-0.036 (0.139)	0.023 (0.911)	0.024 (0.323)
Soybean Oil	0.019 (0.437)	-0.047 (0.055)	0.008 (0.745)	0.014 (0.557)
Soft Wheat	-0.029 (0.226)	-0.104 (<0.01)	0.061 (0.01)	0.074 (<0.01)
Hard Wheat	-0.053 (0.029)	-0.103 (<0.01)	0.083 (<0.01)	0.078 (<0.01)
Oats	-0.028 (0.259)	-0.038 (0.129)	0.047 (0.063)	0.044 (0.078)
Feeder Cattle	-0.078 (<0.01)	-0.096 (<0.01)	0.048 (0.051)	0.034 (0.214)
Live Cattle	-0.059 (0.015)	-0.122 (<0.01)	0.062 (0.011)	0.072 (<0.01)
Lean Hogs	-0.027 (0.273)	-0.058 (0.017)	-0.002 (0.926)	0.00001 (0.998)

Note: *p*-values in parentheses; obtained using Block Bootstrap with 1000 replications

Table 5. MINE statistics

(changes in the *p*-values from the GS test and in illiquidity measures for the same market)

	AM			MN		
	MIC	MIC-ρ^2	MAS	MIC	MIC-ρ^2	MAS
Corn	0.116 (<0.01)	0.115 (<0.01)	0.023 (<0.01)	0.115 (<0.01)	0.114 (0.011)	0.026 (0.021)
Soybeans	0.101 (<0.01)	0.1 (<0.01)	0.033 (0.031)	0.105 (<0.01)	0.104 (<0.01)	0.007 (0.275)
Soybean Meal	0.118 (<0.01)	0.117 (<0.01)	0.012 (0.203)	0.115 (<0.01)	0.114 (<0.01)	0.007 (0.416)
Soybean Oil	0.12 (<0.01)	0.119 (<0.01)	0.016 (0.056)	0.113 (<0.01)	0.112 (<0.01)	0.015 (0.13)
Soft Wheat	0.125 (<0.01)	0.124 (<0.01)	0.012 (0.082)	0.11 (<0.01)	0.106 (<0.01)	0.013 (0.156)
Hard Wheat	0.14 (<0.01)	0.137 (<0.01)	0.026 (0.069)	0.11 (<0.01)	0.103 (<0.01)	0.012 (0.271)
Oats	0.111 (<0.01)	0.11 (<0.01)	0.013 (0.102)	0.104 (<0.01)	0.102 (<0.01)	0.006 (0.319)
Feeder Cattle	0.125 (<0.01)	0.118 (<0.01)	0.012 (0.169)	0.107 (<0.01)	0.104 (0.089)	0.01 (0.154)
Live Cattle	0.138 (<0.01)	0.135 (<0.01)	0.024 (<0.01)	0.108 (<0.01)	0.104 (0.151)	0.01 (0.283)
Lean Hogs	0.115 (<0.01)	0.114 (<0.01)	0.021 (0.015)	0.106 (<0.01)	0.105 (<0.01)	0.03 (<0.01)

Note: *p*-values in parentheses; obtained using Block Bootstrap with 1000 replications

Figure A.1: Logarithmic prices

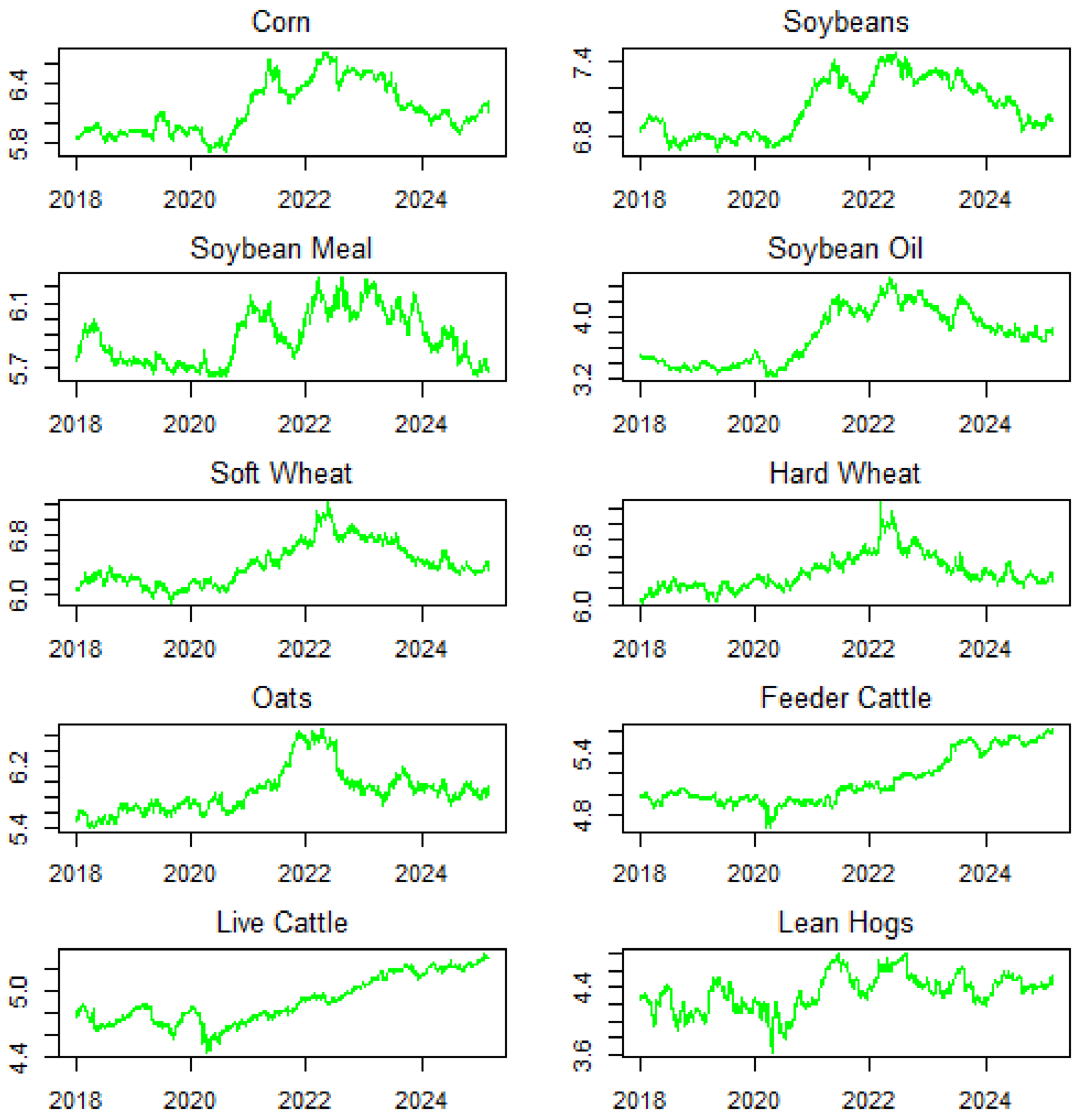

Table A.1: Price returns. Descriptive statistics

Commodity	mean	sd	max	min	skewness	kurtosis	normality
Corn	0.00014	0.017	0.077	-0.191	-1.678 (<0.01)	22.27 (<0.01)	0.887 (<0.01)
Soybeans	0.000032	0.013	0.064	-0.111	-0.669 (<0.01)	8.992 (<0.01)	0.955 (<0.01)
Soybean Meal	-0.00004	0.017	0.075	-0.143	-1.088 (<0.01)	14.269 (<0.01)	0.906 (<0.01)
Soybean Oil	0.00015	0.018	0.073	-0.095	-0.371 (<0.01)	4.922 (<0.01)	0.981 (<0.01)
Soft Wheat	0.0001	0.021	0.197	-0.113	0.566 (<0.01)	8.894 (<0.01)	0.959 (<0.01)
Hard Wheat	0.0001	0.02	0.078	-0.119	0.081 (0.162)	4.77 (<0.01)	0.983 (<0.01)
Oats	0.0002	0.024	0.145	-0.342	-2.236 (<0.01)	33.105 (<0.01)	0.874 (<0.01)
Feeder Cattle	0.0003	0.012	0.113	-0.081	1.057 (<0.01)	16.379 (<0.01)	0.879 (<0.01)
Live Cattle	0.0003	0.012	0.07	-0.156	-1.69 (<0.01)	26.889 (<0.01)	0.831 (<0.01)
Lean Hogs	0.00009	0.028	0.236	-0.268	-0.76 (<0.01)	23.111 (<0.01)	0.762 (<0.01)

Note: *p*-values in parentheses; obtained with Block Bootstrap with 1000 replications.

Table A.2: Illiquidity proxies. Descriptive statistics

	AM				MN			
Commodity	mean	Sd	max	min	mean	Sd	max	min
Corn	0.000003	0.00002	0.0006	0	0.01	0.008	0.118	0
Soybeans	0.000015	0.0001	0.003	0	0.008	0.005	0.057	0
Soybean Meal	0.00002	0.00016	0.005	0	0.009	0.007	0.056	0
Soybean Oil	0.00015	0.0014	0.034	0	0.01	0.008	0.059	0
Soft Wheat	0.00009	0.0008	0.021	0	0.012	0.009	0.103	0
Hard Wheat	0.0003	0.002	0.0467	0	0.012	0.009	0.057	0
Oats	0.0012	0.0052	0.085	0	0.014	0.012	0.159	0
Feeder Cattle	0.000004	0.000007	0.0001	0	0.006	0.005	0.076	0
Live Cattle	0.000002	0.0006	0.00005	0	0.005	0.005	0.088	0
Lean Hogs	0.000004	0.00003	0.0006	0	0.01	0.008	0.106	0