International Review of Financial Analysis 105 (2025) 104424

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Market efficiency across intra-daily sampling frequencies for Brent crude oil futures

Erik Smith-Meyer [a], Erik Haugom [a,*], Christian Oliver Ewald [a,b,c]

[a] Department of Business Administration, Inland School of Business and Social Sciences, University of Inland Norway, Lillehammer, 2604, Norway
[b] Adam Smith Business School—Economics, University of Glasgow, Glasgow, G12 8QQ, UK
[c] Department of Mathematics and Mathematical Statistics, Umeå University, Umeå, 90187, Sweden

ARTICLE INFO

Keywords:
Intercontinental Exchange (ICE)
Market efficiency
Sample frequency
Adjusted market inefficiency magnitude

ABSTRACT

We study market efficiency for high-frequency Brent Crude oil futures prices across intra-daily sampling frequencies ranging from one minute to two hours using a sample period from 2006 to 2021. The efficiency dynamics of Brent crude oil futures prices are scrutinized over time using rolling estimation windows. We also propose to study intra-daily market efficiency using a signature plot across sampling frequency. Our results show substantial differences in market efficiency at the intra-daily level. At very high sampling frequencies (less than 10 min), the market is on average inefficient. For lower sampling frequencies, efficiency in Brent oil futures generally improves over the examined sample period.

1. Introduction

Brent crude oil futures traded on the Intercontinental Exchange (ICE) are considered the global benchmark in oil trading. The price movements in these futures contracts are closely followed by investors and physical traders operating in the oil market. They also interest the wider business and investment community as oil prices influence the equity markets (Sim & Zhou, 2015). According to Sadorsky (2006), Brent crude oil is by far the most important commodity traded worldwide. Hence, the efficiency (or lack thereof) in the oil market has major implications and has been studied extensively for both Brent crude oil and WTI crude oil using daily or lower frequency data (see, e.g., Arshad et al. (2021), Charles and Darné (2009), Ghazani and Ebrahimi (2019), Okoroafor and Leirvik (2022), and Tabak and Cajueiro (2007)).

In recent decades, algorithmic trading and other short-term trading activities have substantially increased intra-daily trading volumes. There is, therefore, a growing need for a better understanding of how efficient the world's most important commodity market is at the intra-daily level. Despite the growing importance and relevance of market efficiency in high-frequency oil prices, the vast majority of existing research uses daily or lower-frequency data. One recent but rare exception is Ftiti et al. (2021), who examine the efficiency in WTI crude oil- and natural gas prices from 2007 to 2010 using multifractal analysis and five-minute sampling as the only intra-daily sampling frequency. The present study, therefore, fills important gaps in the literature as it is the first to examine market efficiency in crude oil across sampling frequency using high-frequency data. Specifically, our article contributes to answering several conceptual questions regarding the efficiency in the intra-daily Brent Crude oil market:

- To what degree are high-frequency (intra-daily) ICE Brent Crude oil futures prices efficient?
- Does the degree of market efficiency vary across intra-daily sampling frequency?
- Have the dynamics of the market efficiency on the intra-daily level changed over time?

The Efficient Market Hypothesis (EMH) posits that financial asset prices reflect all relevant information available (Fama, 1970). The hypothesis comes in three 'forms': weak, semi-strong, and strong. Researchers tend to focus on weak-form and semi-strong-form efficiency because it is generally accepted that the strong form of the efficient market hypothesis does not hold, as private and insider information generally leads to arbitrage opportunities. The weak-form efficiency, which we focus on in the current study, suggests that asset prices are unpredictable on the basis of their past values.

Weak-form efficiency has been studied extensively within stock markets (see e.g., Lim et al., 2008; Xu et al., 2023).[1] In recent years, several studies have focused on the relationship between intra-daily (high-frequency) or algorithmic trading and market efficiency for such markets (see e.g., Chakrabarty et al., 2022; Yuferova, 2024). The topic

* Corresponding author.
E-mail address: erik.haugom@inn.no (E. Haugom).

[1] See Lim and Brooks (2011) for a survey of the empirical literature.

https://doi.org/10.1016/j.irfa.2025.104424
Received 31 January 2025; Received in revised form 25 May 2025; Accepted 16 June 2025
Available online 5 July 2025
1057-5219/© 2025 The Author(s). Published by Elsevier Inc. This is an open access article under the CC BY license (http://creativecommons.org/licenses/by/4.0/).

has also been examined in a range of other markets such as precious metals (Charles et al., 2015), coffee and cocoa (Sabuhoro & Larue, 1997), wine (Shynkevich, 2025), copper (Zhang et al., 2024), electricity (Haugom & Ullrich, 2012), and crypto (Bariviera, 2017; Wang & Gacesa, 2023) to mention a few.

For the oil markets, the early literature focused on whether the infrequently adjusted so-called OPEC official prices behaved like efficient contract prices (see e.g., Gately et al. (1977) and Green and Mork (1991)). Green and Mork (1991) found that the efficiency hypothesis was rejected for the sample period 1978–1985, but offered some evidence that efficiency had improved over time. In the 2000s, the research started to focus on long-range dependence in crude oil returns and their volatility (see e.g., Alvarez-Ramirez et al. (2002), Serletis and Andreadis (2004) and Tabak and Cajueiro (2007)). The general findings were that crude oil markets had become more efficient over time and that the volatility of oil prices is highly persistent and capable of predicting return volatility in many other industries (Wang et al., 2018).

In a more recent study, Ghazani and Ebrahimi (2019) tested the Adaptive Market Hypothesis on WTI, Brent, and OPEC basket data using rolling windows of various lengths. They also included two tests for linear- and non-linear dependence and found that the WTI and Brent markets, in general, are efficient, while the OPEC basket was found to be inefficient, particularly when applying a 500-day rolling window. Arshad et al. (2021) used daily data from 1996 to 2018 to investigate whether crude oil prices are weak-form efficient during different economic cycles. Although there are variable patterns over the sample period, their main finding is that Brent crude oil prices are weak-form efficient. The results are also confirmed in a robustness check using weekly data.

The only study using high-frequency (intra-daily) data to study efficiency in the crude oil market is that performed by Ftiti et al. (2021). They used five-minute prices for WTI crude oil and natural gas futures contracts from 2007 to 2010 and examined persistence in returns using a de-trended moving average, from which they calculated the Hurst exponent. The Hurst exponent is a measure of the long-term persistence of returns and is thus an indication of market efficiency. Their main finding was that the oil and gas markets are inefficient for short time horizons (below two weeks) and that both markets exhibit multifractal behavior that increases in post-crisis periods. They also show that multifractality in lower-frequency data may be more biased than that in high-frequency, intra-daily data.

Our study differs from Ftiti et al. (2021) in several important ways. First, while Ftiti et al. (2021) only examine the five-minute sampling frequency, we evaluate all sampling frequencies between one- and 120 min in our analysis. This extension contributes in itself to a more comprehensive understanding of how market efficiency for crude oil prices behaves at the intra-daily level. Analyzing a range of sampling frequencies instead of just one allows us to study how quickly oil prices respond to new information. We illustrate the speed of price adjustment in what we call a *signature plot* of a given efficiency measure across intra-daily sampling frequency.

Second, in addition to the Hurst exponent used by Ftiti et al. (2021) we implement both the Variance Ratio (VR) test of Lo and MacKinlay (1988) and the Runs test by Wald and Wolfowitz (1940). We also include the results of a new and simple-to-implement measure of market efficiency proposed by Tran and Leirvik (2019) called the Adjusted Market Inefficiency Measure (AMIM). This method is computationally cheap and the measure is calculated based on standardized coefficients, simplifying the comparison of market efficiency across markets, time periods, or sampling frequencies.[2]

Third, we examine the efficiency in high-frequency Brent Crude oil futures from 2006 to 2021 (16 years) – almost 13 years more of high-frequency data compared with the study by Ftiti et al. (2021). Finally, while Ftiti et al. (2021) examined the efficiency in the oil market using the CL1 index[3], we use real transaction-level trading data for the front-month Brent Crude futures contract traded at the Intercontinental Exchange (ICE).

We document two key findings. First, market efficiency varies substantially across intra-daily sampling frequency. The signature plots of the various market efficiency measures show an exponential pattern with the highest inefficiency observed for sampling frequencies of between one and 10 min. The pattern is consistent across the measures used to assess market efficiency.

Second, the results are somewhat mixed when studying market efficiency at the very highest sampling frequency (one minute) using rolling windows over the entire sample period. The VR test and the AMIM measure suggest that the market has become somewhat more inefficient over time, particularly in the years after 2016. The Hurst exponent, however, suggests that efficiency has improved over time and that the market is generally efficient for the most recent years. The results of the Runs test show that it is only in the very first part of the sample period (2006–2009) that we are close to rejecting the null hypothesis of random and independent price changes. For the rest of the sample period, the Runs test supports weak form market efficiency.

The rest of the paper is organized as follows. In Section 2 we present the tests used to assess market efficiency in this study. The data and preliminary analyses are presented in Section 3 while our main results are presented in Section 4. Section 5 concludes and offers some directions for future research within the given topic area.

2. Methodology

In the present study, we focus on testing the predictability of high-frequency Brent Crude oil returns based on past price changes. For this purpose, a range of statistical tests can be employed. Most of the tests have in common that the objective is to detect serial dependence in the returns (Lim & Brooks, 2011). We apply several such tests. First, we follow Ftiti et al. (2021) and calculate the Hurst Exponent to examine market efficiency in high-frequency Brent Crude Oil prices. Second, we implement the Variance Ratio (VR) and the Runs tests, both widely used in the existing literature to assess market efficiency. We also include the results of a recently proposed and simple-to-implement measure called the Adjusted Market Inefficiency Measure.

2.1. The Hurst exponent

The Hurst exponent (H) is a statistical measure used to evaluate the long-term memory or dependence in a time series. It originates from hydrology and was introduced by Hurst (1951), but has since been widely applied in finance and economics, early on by Mandelbrot (1971). The Hurst exponent can be used to test for deviations from the random walk hypothesis and to assess market efficiency.

The Hurst exponent is originally estimated using the rescaled range (R/S) analysis. For a time series $X = \{x_1, x_2, \ldots, x_T\}$, the steps to compute the Hurst exponent are as follows:

- Divide the time series into k non-overlapping segments of length n where the starting number of elements in n equals 2.
- For each segment, r, calculate the mean ($\bar{x}_{r,n}$), the standard deviation ($S_{r,n}$), and the cumulative deviations from the mean:

$$Y(r,n) = \sum_{i=1}^{n}(x_{r,i} - \bar{x}_{r,n}) \quad (1)$$

[2] When using the AMIM measure, there are important considerations regarding the number of observations. We elaborate on this in Section 2, where we focus on the methodology.

[3] The CL1 index is a continuous contract based on the front-month futures contract.

- Compute the range $R(r,n)$ as the difference between the maximum and minimum cumulative deviation for each segment:

$$R(r,n) = \max_{1\le t\le n} Y(r,n) - \min_{1\le t\le n} Y(r,n). \quad (2)$$

- Normalize the range for each segment:

$$(R/S)_r = \frac{R(r,n)}{S(r,n)}, \quad . \quad (3)$$

- Take the average of the k rescaled ranges for segment size n:

$$(R/S)_n = \frac{1}{k}\sum_{r=1}^{k}(R/S)_r \quad (4)$$

- The value of the n and $(R/S)_n$ are stored.
- Increase n by one and repeat the above steps. This is done until the dataset is exhausted, or a maximum value of n is hit.
- Take the logarithm of n and $(R/S)_n$ vectors.
- Estimate the Hurst exponent by fitting the following power-law relationship:

$$E\left[\frac{R(n)}{S(n)}\right] \sim Cn^H. \quad (5)$$

This is done by fitting the following regression model on the data:

$$ln(R/S) \sim ln(C) + H\ ln(n) \quad (6)$$

A pure random walk would yield a Hurst exponent equal to 0.5. If the slope from the equation is larger than this number, then this would be a sign of *persistent* or trending behavior, where past movements are likely to continue in the same direction, suggesting market inefficiency. If the slope's value is below 0.5 then the time series shows *anti-persistent* or mean-reverting behavior, where past movements are likely to reverse. This also indicates market inefficiency. The Hurst exponent assumes that the time series of interest is stationary and has finite variance. Violating these assumptions can affect reliability and induce misleading estimates of the Hurst exponent. The accuracy of the Hurst exponent is also sensitive to the length of the time series, where short time series can result in biased results (Barunik & Kristoufek, 2010; Weron, 2002).

2.2. Variance ratio test

The Variance Ratio (VR) test introduced by Lo and MacKinlay (1988) compares the variance of multi-period returns to the variance of single-period returns under the null hypothesis that the variance of returns scales linearly with the time horizon.

Let P_t represent a time series of asset prices, and let the return series be defined as:

$$r_t = P_t - P_{t-1}, \quad t = 2,\dots,T \quad (7)$$

The k-period return is then given by:

$$R_k = P_t - P_{t-k}, \quad t = k+1,\dots,T \quad (8)$$

Under the random walk hypothesis, the variance of k-period returns should be proportional to k times the variance of single-period returns:

$$\mathrm{Var}(R_k) = k \cdot \mathrm{Var}(r_t). \quad (9)$$

The null hypothesis of the test is:

$$H_0 : \mathrm{Var}(R_k) = k \cdot \mathrm{Var}(r_t), \quad (10)$$

while the variance ratio $VR(k)$ is defined as:

$$VR(k) = \frac{\mathrm{Var}(R_k)}{k \cdot \mathrm{Var}(r_t)}. \quad (11)$$

The test statistic for the variance ratio is computed as:

$$Z = \frac{VR(k) - 1}{\sigma_{VR}}, \quad (12)$$

where σ_{VR} is the standard error of the variance ratio, given by:

$$\sigma_{VR} = \frac{2(2k-1)(k-1)}{3kT}, \quad (13)$$

and T is the total number of observations in the time series.

The test statistic Z is asymptotically standard normal under the null hypothesis and the decision rule is to reject H_0 if its absolute value exceeds the critical value at the chosen significance level α. If $VR(k) = 1$, the market is weak-form efficient and the returns follow a random walk. $VR(k) > 1$ indicates a positive serial correlation (momentum) in returns, suggesting inefficiency. $VR(k) < 1$ suggests a negative serial correlation (mean reversion) and is also an indication of inefficiency. The VR test assumes stationarity, however the time series is allowed to be conditionally or unconditionally heteroscedastic (Kim & Shamsuddin, 2008). The test also presumes no serial correlation beyond the lag structure considered in the empirical analyses and the test may exhibit bias in small samples (Charles & Darné, 2009; Lo & MacKinlay, 1988). We assess the stationarity of return series at multiple intraday frequencies – specifically 1, 5, 10, 20, 40, 90, and 120 min intervals – using both the Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. The ADF test results indicate rejection of the null hypothesis of a unit root across all time intervals, suggesting that the series are stationary. In addition, the KPSS test does not reject the null hypothesis of stationarity for any of the series. Taken together, the findings from both tests provide consistent indications that none of the return series exhibits signs of nonstationarity.

2.3. The Runs Test

The Runs Test, also known as the Wald–Wolfowitz Runs Test (Wald & Wolfowitz, 1940), is a non-parametric statistical test used to evaluate the randomness of a sequence, such as financial returns or price changes. The test assesses whether the observed sequence of positive and negative price changes exhibits a pattern or randomness.

A *run* is defined as a sequence of consecutive observations with the same sign, such as consecutive positive or negative returns. The null hypothesis (H_0) of the Runs Test states that the sequence of price changes is random and independent, which aligns with the assumption of weak-form market efficiency. The alternative hypothesis H_1 suggests that the sequence is non-random, implying potential market inefficiencies.

The expected number of runs ($E(R)$) under the assumption of randomness is calculated as:

$$E(R) = \frac{2n_1n_2}{n_1+n_2} + 1, \quad (14)$$

where n_1 is the number of positive returns, n_2 is the number of negative returns, and $n = n_1 + n_2$.

The standard deviation of the number of runs (σ_R) is given by:

$$\sigma_R = \sqrt{\frac{2n_1n_2(2n_1n_2 - n)}{n^2(n-1)}}. \quad (15)$$

The test statistic (Z) is then calculated as:

$$Z = \frac{R - E(R)}{\sigma_R}, \quad (16)$$

where R is the observed number of runs.

If the calculated Z -statistic lies outside the critical range (e.g., $[-1.96, 1.96]$ for a 5% significance level), the null hypothesis of randomness is rejected. This suggests that the time series exhibits non-random patterns, such as positive autocorrelation (trending behavior) or negative autocorrelation (mean-reverting behavior), indicating market inefficiencies. The test assumes that the observations used should be randomly sampled from the population (Wald & Wolfowitz, 1940). We ensure this by using fixed sampling intervals and appropriate interpolation methods, as described further in Section 3.

2.4. The Adjusted Market Inefficiency Measure (AMIM)

The AMIM measure is constructed in four steps. The steps are described in detail by Tran and Leirvik (2019), and we refer interested readers to their article for a thorough explanation and reasoning behind the calculations. In the present paper, we focus solely on presenting the calculations needed to implement the AMIM measure. The four steps are:

(i) Run an AR(*q*) model and normalize the autocorrelation coefficients
(ii) Calculate the market inefficiency magnitude (MIM)
(iii) Building confidence intervals for the MIM
(iv) Calculate the Adjusted Market Inefficiency Magnitude (AMIM)

2.4.1. Step-by-step calculation of AMIM

Step 1.1: Run the AR(q) model

Run an autoregressive model of order q (AR(q) model) on the log-returns as defined in Eq. (17). The lag length (q) should be decided based on Akaike's Information Criterion (AIC). In our study, we choose a maximum lag-length of 45 to limit the computational complexity.

$$r_t = \alpha + \sum_{i=1}^{q} \beta_i r_{t-i} + \epsilon_t. \tag{17}$$

Now we have a vector of estimated slope coefficients, $\boldsymbol{\beta}$'s, and an estimated covariance matrix, $\boldsymbol{\Sigma}$. *Step 1.2: Normalize the autocorrelation coefficients*

After estimating (17), the auto-regressive coefficients shall be normalized using the following procedure:

- Estimate the Cholesky decomposition of $\boldsymbol{\Sigma}$, $\boldsymbol{\Sigma} = \mathbf{L}\mathbf{L}^T$
- Calculate the standardized beta vector, β^*, by left multiplying the β's with the inverse of the lower triangular Cholesky matrix: $\beta^* = L^{-1}\beta$

Step 2.1: Calculate the MIM

The MIM for time period t is calculated as follows:

$$MIM_t = \frac{\sum_{i=1}^{q} |\beta_{i,t}^*|}{1 + \sum_{i=1}^{q} |\beta_{i,t}^*|}. \tag{18}$$

where $\beta_{i,t}^*$ is the standardized coefficients from Eq. (17).

Step 3.1: Building confidence intervals for the MIM

The confidence intervals to use for the MIM are unique for the number of lags used in the autoregressive model (Eq. (17)). Tran and Leirvik (2019) have computed the confidence intervals to use for a wide number of lags and these are presented in Table A.1 in Appendix. As the confidence intervals are based on standardized coefficients, they can be used for the calculation of AMIM regardless of the data set used in the empirical analyses.

Step 4.1: Calculate AMIM

Given the lag length, q, from step 1, the relevant confidence interval from Table A.1 is chosen. That confidence interval, R_{CI}, is then used to calculate the AMIM:

$$AMIM_t = \frac{MIM_t - R_{CI}}{1 - R_{CI}}. \tag{19}$$

Because MIM_t is always less than one, the value of $AMIM_t$ is always less than one as well. A positive value of AMIM enables us to reject the null hypothesis of market efficiency.

Note that AMIM is highly affected by the number of observations used in the estimations. As the sample size gets larger, the theoretical standard error of the regression estimates gets smaller. Hence, for a fixed sample period there are twice as many one-minute returns as two-minute returns, ten times as many one-minute returns as 10 min returns, and so forth. When comparing inefficiency across sampling frequency, we therefore make sure to include the same number of observations for each AMIM estimation. The details of the approach we use are presented in Section 4.

3. Data and preliminary analysis

The data consist of high-frequency, tick-by-tick transaction-level data, for the front-month Brent Crude oil futures contracts traded at the Intercontinental Exchange (ICE) from January 3, 2006, to October 29, 2021, for a total of 4048 trading days.[4] The front-month contract is by far the most heavily traded Brent contract at ICE, with average daily trading volume almost 11% higher than the second month contract, and 90% higher than the third-month contract. Such trading pattern is common in U.S. and European markets, but not in Chinese markets. In China, investors typically prefer longer-dated contracts with specific maturities both for agricultural commodities and crude oil (see e.g., Yang et al. (2021) and Yu et al. (2023)).

The ICE Brent Crude futures contract is a deliverable contract based on the Exchange of Futures for Physical (EFP) mechanism with an option to cash settle. The price is given in US dollars and cents per barrel with a minimum price fluctuation of $0.01 per barrel, but the contract size is 1000 barrels (42,000 US gallons). The trading hours for Brent Crude Oil futures are from 1.00 AM to 11.00 PM London time. This means that the contract is open for trading in 22 out of 24 h of the day.

There have been some minor changes in the contract specifications over time. For the sample period ranging from January 2006 to February 2016, trading in each contract ceased at the end of the designated period of settlement on the Business Day (a trading day that is not a public holiday in England and Wales) immediately preceding (i) either the fifteenth day before the first day of the contract month, if this fifteenth day is a Business Day, or (ii) if this fifteenth day is not a Business Day, the next preceding Business Day (ICE, 2023). From March 2016 to the end of the sample period, trading ceased at the end of the designated settlement period on the last Business Day of the second month preceding the relevant contract month (e.g. the March contract will expire on the last Business Day of January). If the day on which trading is due to cease would be either (i) the Business Day preceding Christmas Day or (ii) the Business Day preceding New Year's Day, then trading shall cease on the next preceding Business Day (see ICE (2023) for further details).

Fig. 1 illustrates the trading volume measured as the total number of traded contracts per trading day (upper panel) and the average number of traded contracts across all trading hours the market is open (lower panel). The upper panel shows a clear positive trend in the total trading volume over the sample period. We also note an increase in the volatility of the trading volume, with the highest daily levels reached in early 2020, corresponding to the outbreak of the Covid-19 pandemic. At the intra-daily level, the trading volume is highest during the regular trading hours of the European and U.S. market with the highest level observed during the early trading hours of the U.S. market.

From the transaction level data, we create equally-spaced intra-daily data with a sampling frequency of between one and 120 min using the previous tick interpolation method (Dacorogna et al., 2001). The method is simple to implement as it only involves taking the last available observation before the minute of interest. Though other methods to construct equally spaced data have been proposed in the literature[5] offer a theoretical argument for choosing the previous tick method over alternatives, such as the linear interpolation method. We therefore follow them, and many others, and use the previous tick interpolation method when constructing the equally-spaced data used in the main empirical analyses.

When working with high-frequency data microstructure noise can be an issue due to bid–ask bounce, discreteness of prices, liquidity effects, and more (Martens & van Dijk, 2007). In practice, many

[4] The same transaction-level data was used by Ewald et al. (2023) and a shorter sample period of the same data has been used by Haugom et al. (2014).

[5] See e.g., Andersen and Bollerslev (1998) and Dacorogna et al. (2001).

Table 1
Descriptive statistics.

Sample frequency	Mean	St. Dev.	Max	Min	Skewness	Kurtosis	Zero-returns
1-min	−0.00000%	0.0007	13.14%	−10.27%	1.1	543.4	24.9%
5-min	−0.00002%	0.0016	7.72%	−6.21%	0.5	75.6	13.0%
10-min	−0.00004%	0.0022	14.18%	−7.18%	0.8	86.4	9.7%
20-min	−0.00008%	0.0030	14.33%	−8.41%	0.5	53.4	7.2%
40-min	−0.00016%	0.0042	15.05%	−13.58%	0.3	48.2	4.9%
90-min	−0.00036%	0.0063	14.50%	−7.31%	0.3	21.0	3.2%
120-min	−0.00048%	0.0072	12.81%	−9.11%	0.3	15.5	2.3%
Intra-daily	−0.00363%	0.0202	20.78%	−19.94%	0.1	8.1	0.3%

previous studies therefore use sampling frequencies between 5 and 30 min to balance increased accuracy with microstructure frictions (see e.g., Andersen et al. (2003), Fleming et al. (2003) and Patton and Sheppard (2015)). For highly liquid assets, such as S&P futures and Brent Crude oil futures, microstructure friction first and foremost becomes a significant problem at very high sampling frequencies, typically in the range of seconds. Bandi and Russell (2006), for example, show that noise effects decay as sampling intervals exceed 1-5 min. They also specifically state that microstructure friction is a bigger issue for assets with low liquidity. Ait-Sahalia and Yu (2008) document that more liquid assets have lower noise and noise-to-signal ratios from their high-frequency returns, while Hansen and Lunde (2006) state that the bias in realized volatility calculations gets pronounced when sampling more frequently than every 30 s for liquid assets. To address potential issues related to market microstructure, we avoid going beyond the one-minute sampling frequency in the present study.[6]

Though Brent crude oil futures can be traded for 22 out of the 24 h of the day (from 01.00 AM to 11.00 PM London time), there is still informational build-up during the hours the market is closed. This makes the properties of overnight returns differ from those sampled at the intra-daily level (see e.g., Branch and Ma (2012) and Hansen and Lunde (2005)). Hence, when studying intra-daily market efficiency, the overnight return between trading days could influence the results if not handled properly. In our study, we are first and foremost interested in examining how market efficiency behaves at the intra-daily level and we therefore only use returns calculated from within the same trading days when constructing the efficiency measure. Returns between trading days, or so-called *overnight returns*, are not used in any of the empirical analyses.

Table 1 presents descriptive statistics for the returns calculated from various sampling frequencies. Across all sampling frequencies, the returns exhibit some skewness and high excess kurtosis. These properties are well-documented in extant research on high-frequency finance (see Dacorogna et al. (2001), Haugom (2011) and Haugom et al. (2014)). At the very highest sampling frequency (one minute), a quarter of the returns are zero returns (no price change). A vast majority of these stem from outside the main trading hours in the major trading regions (London and New York) and particularly from the early sample period when the liquidity was lower (c.f. Fig. 1).

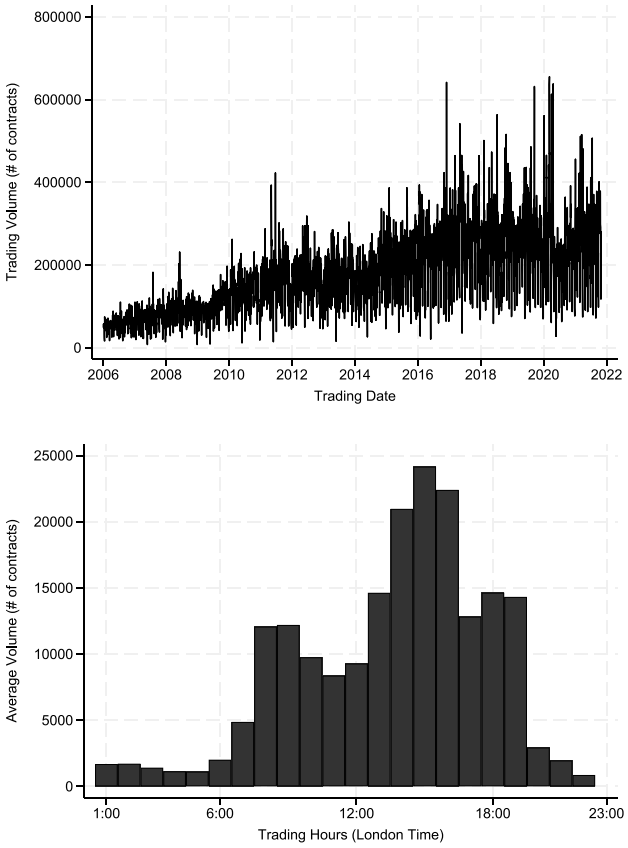

Fig. 1. Trading volume measured in total number of contracts traded per trading day (upper panel) and average number of contracts traded across intra-daily trading hours (lower panel).

Fig. 2 illustrates daily closing prices (upper panel) and corresponding daily log returns (lower panel). From the plot, we clearly observe the high price variation and volatility clustering of the returns over time. Oil futures experienced particularly high volatility levels during the great financial crisis in 2008–2009 and during the Covid-19 pandemic starting in early 2020.

4. Results

4.1. Market efficiency across sampling frequency

We start by examining efficiency across the sampling frequency of Brent Crude Oil futures prices using the four measures described in Section 2. For each sampling frequency, we estimate the various measures based on 900 observations in non-overlapping windows. This is similar to the approach of Tran and Leirvik (2019), who used daily data with each year as a separate window. The values of the various efficiency measures for all windows are then averaged over the entire sample period.

[6] We have compared the one-minute prices (and returns) based on the previous tick interpolation method with the average price of all transaction prices for every minute in the sample. The average of all the transaction prices within a given minute would be similar to the so-called mid-quotes prices as every transaction in the sample is either buyer- or seller-initiated. Our results suggest that the one-minute prices based on the two methods are almost identical. The mean one-minute return based on the previous tick method is 75.49111 and 24.92006. The corresponding numbers based on the so-called mid-quote prices are 75.49109 with a standard deviation of 24.92005. This suggests that microstructure noise is not an issue for the highly liquid Brent Crude oil prices at the one-minute sampling frequency. If going beyond the one-minute frequency, however, using mid-quote prices could be used as an approximation of the efficient price to mitigate noise related to bid–ask bounce effects (see e.g., Lee and Mykland (2012) and Clinet and Potiron (2021)).

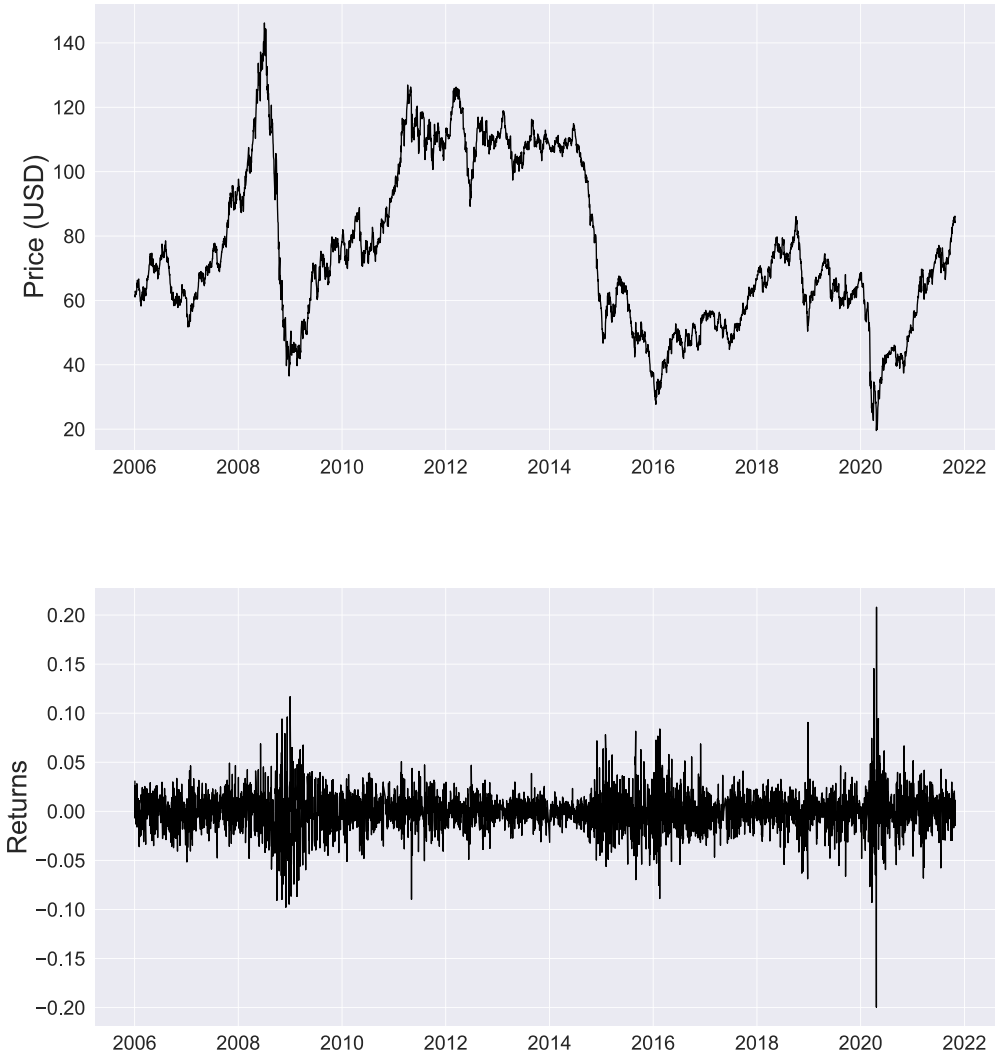

Fig. 2. Daily Brent Crude Oil futures close prices (upper panel) and corresponding daily close-close log-returns (lower panel).

The key results are presented in Fig. 3, we refer to these plots as *signature plots of market efficiency*. The term *signature plot* has been used to assess what sampling frequency to use in the calculation of realized volatility (see e.g., Andersen et al. (1999)). In that case, the signature plot depicts the average realized volatility across sampling frequency. We depict the average estimate of market efficiency across sampling frequency and thus use the notion *signature plot of market efficiency* to describe it. The signature plot quickly reveals whether market efficiency increases, decreases, or is unaffected by the sampling frequency. A signature plot approaching zero for AMIM, for example, would indicate that the market is more efficient at lower sampling frequencies (such as 60 or 120 min) and vice versa.

The results show that market efficiency, as calculated by the four efficiency measures, is strongly dependent on intra-daily sampling frequency. Fig. 3 indicates stronger inefficiency in Brent Crude Oil futures for the very high sampling frequencies (from one to 10 min) when compared with the results for the lower sampling frequencies (from 10 to 120 min). Market efficiency also exhibits an exponential pattern across sampling frequencies, with the biggest changes occurring for sampling frequencies between one and 10 min. These findings are robust across the four measures used to assess market efficiency.

High-frequency trading (HFT) introduces complex dynamics into financial markets that can lead to inefficiencies. The primary causes of these inefficiencies typically stem from technological advances, behavioral biases, and regulatory frameworks that interact in ways that can distort market operations. One significant cause of inefficiencies arises from the rapid execution of trades by high-frequency traders, which can disrupt traditional market mechanisms. Aït-Sahalia and Saglam (2013) present a model indicating that discrepancies in the speed of trade execution can give HFTs an informational advantage, leading to adverse selection effects where other market participants face a higher risk of trading at suboptimal prices. This unfair advantage may result in liquidity imbalances, as slower traders may find themselves systematically disadvantaged, leading to inefficiencies in pricing.

The phenomenon of "liquidity hoarding" is another contributor to market inefficiency. Gale and Yorulmazer (2013) discuss how financial entities, when faced with uncertainty, might withhold liquidity, resulting in heightened asset price volatility. This hoarding behavior can exacerbate market dislocations, further hampering effective price discovery and leading to inefficient market conditions.

Behavioral factors compound these issues, as retail investors often react irrationally to market signals exacerbated by HFT activities. Yan et al. (2022) argue that the interaction between high-frequency trading and the behavior of retail investors in emerging markets can lead to increased price turbulence and asymmetrical information distribution, contributing significantly to market inefficiencies. This interaction means that significant price movements driven by HFT are not always based on fundamental valuations, thus destabilizing the market.

Moreover, the introduction of HFT has been noted to sometimes slow down the overall price discovery process, as shown in the research

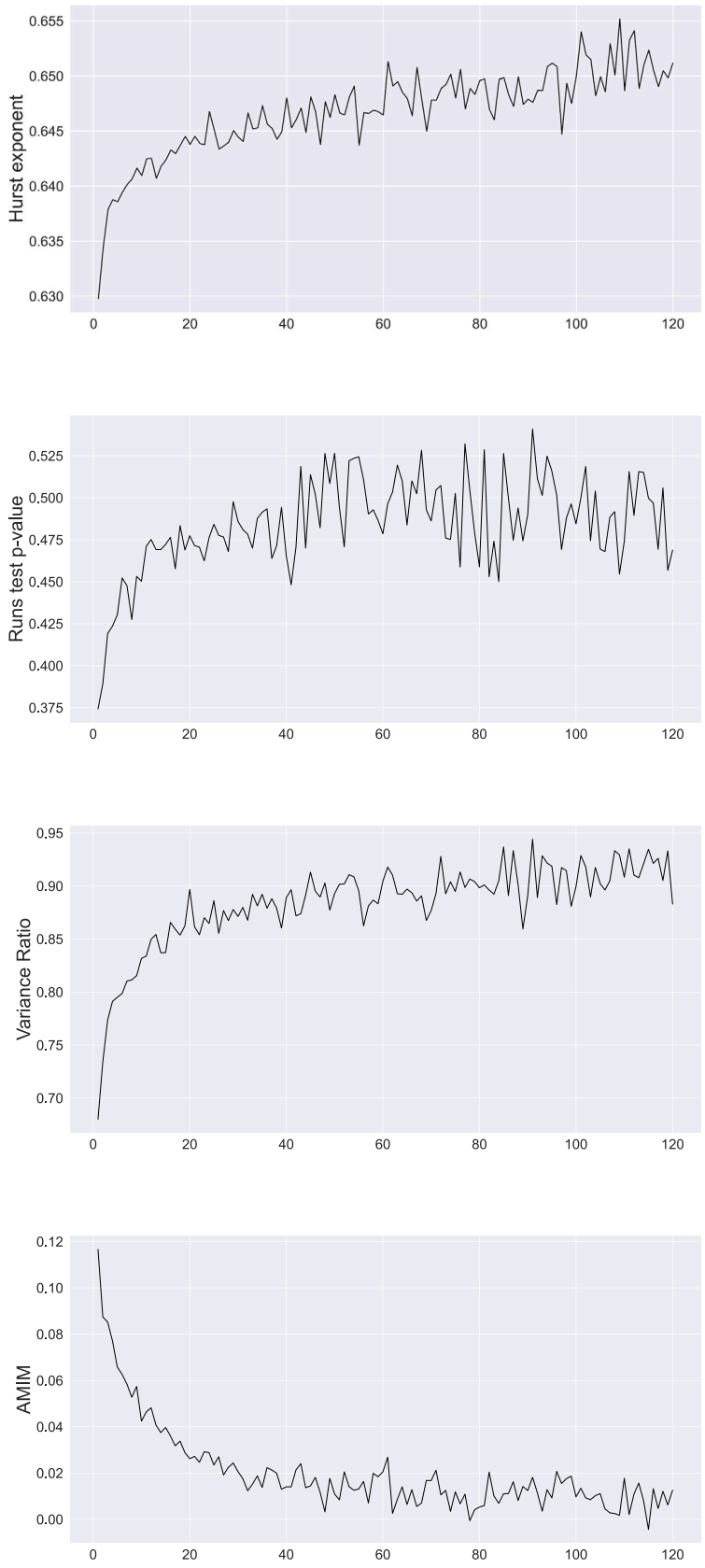

Fig. 3. Signature plots of market efficiency. Average of rolling 900-period estimates of the various efficiency measures across intra-daily sampling frequencies from one- to 120 min.

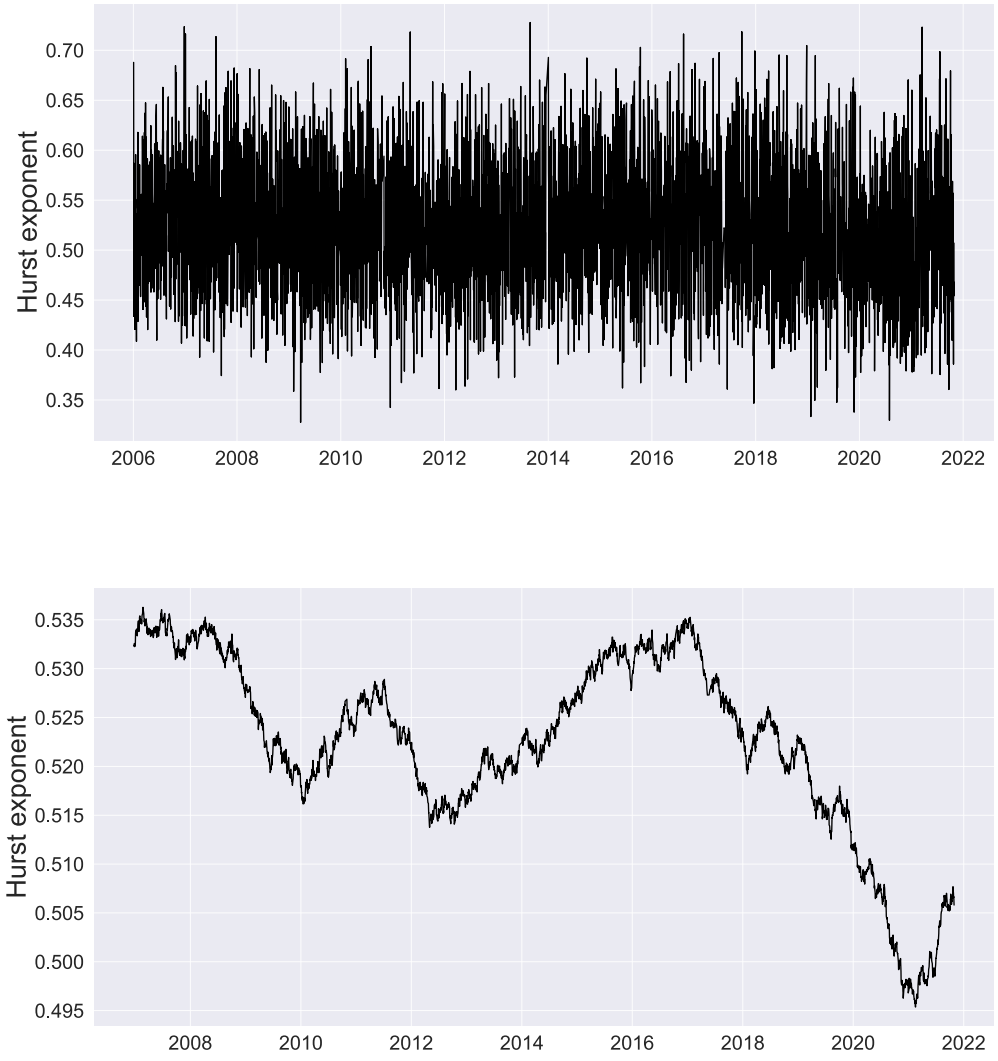

Fig. 4. Daily Hurst exponent calculated using a one-minute sampling frequency (upper panel) and corresponding 252-days rolling average (lower panel).

by Wan and Yang (2017). Positive feedback trading among high-frequency traders can create a dichotomy in market quality, enhancing liquidity while simultaneously hindering the efficiency of price discovery. Such mixed effects indicate a complex interplay where liquidity improves in the short term, but inefficiency persists in the broader price formation process.

4.2. Market efficiency over time

To further examine how efficiency at the intra-daily level behaves, we also calculate the within-day version of the various efficiency measures for the highest sampling frequency (one minute) for all days in the sample period and corresponding 252-days rolling averages of these estimates. 252 days corresponds to approximately one year of trading and is commonly used to analyze the dynamic behavior of asset prices, returns, or volatility (see e.g., Aloui et al. (2016) and Park and Newaz (2023)). The results are illustrated in Figs. 4 to 7.

Let us focus first on Fig. 4. The upper panel shows that there is substantial variation in the daily estimates of the Hurst exponent, with values ranging from approximately 0.35 to 0.70. A Hurst exponent greater than 0.5 suggests persistence (trend) in the returns, while a value of less than 0.5 suggests mean reversion. However, it would only be possible to exploit patterns in trading if there is persistence in the estimates over time. In the lower panel, a one year (252 trading days) rolling average of the daily values from the upper is depicted over the entire sample period. The results suggest that some persistence was present in the Brent Crude futures returns until 2020 and that momentum-based strategies could be used to exploit trends. From 2020 (Covid-19), the rolling average of the daily Hurst exponent is close to 0.5 (slightly below for a short period of time), indicating an efficient market.

In Fig. 5 the corresponding results for the Runs test are illustrated. The upper panel shows the p-value of the test for each day in the sample period. The lower panel illustrates the 252-days rolling average. Though there are days where we can reject the null of market efficiency, particularly at the beginning of the sample (upper panel), the average p-value does never go below 0.05 for a single year in total. The development in the average p-value of the Runs test again suggest that the market has become more efficient over time.

The results for the Variance Ratio (VR) test are presented in Fig. 6, and diverge somewhat from the previous two tests. At the beginning of the sample period, the rolling-averages of the VR test are closer to one ($VR \approx 1$: market is efficient) when compared to later sample periods. However, VR-test results of less than one suggest anti-persistence (mean reversion), and the general pattern, therefore, aligns with the results of the Hurst exponent. The mean-reverting behavior of the returns seems to become stronger over time and particularly so for later sample periods.

The results for the AMIM measure of market efficiency are presented in Fig. 7. The upper panel shows that a substantial number of days

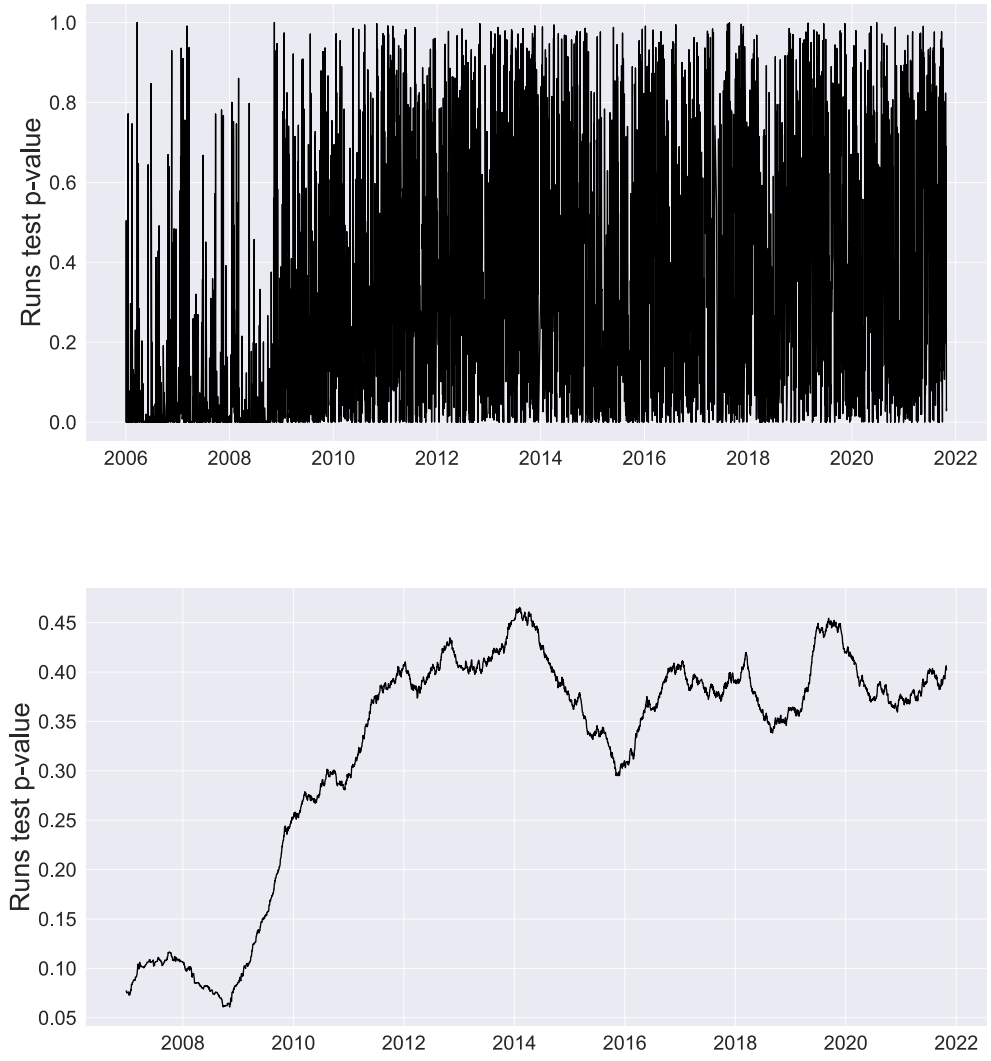

Fig. 5. Daily Runs test calculated using a one-minute sampling frequency (upper panel) and corresponding 252-days rolling average (lower panel). The Runs test is calculated with mean as cutoff.

are estimated to be significantly inefficient at the one-minute sampling frequency. AMIM values between zero and 0.2 are most common, though the inefficiency measure reaches almost 0.8 for some days late in the sample period. The one-year (252 days) rolling average of daily AMIM shows that the Brent Crude oil market, on average, is significantly inefficient. We also note that the AMIM varies around 0.15 for the first half of the sample period, but that it after 2016 has increased substantially and been above 0.30, on average, for most of the time after 2020.

The finding of increased market inefficiency for the one-minute sampling frequency over time may seem counterintuitive and goes against the idea that markets should become more efficient as they mature (Haugom & Ullrich, 2012). As noted by Lim and Brooks (2011), however, it is not unreasonable to expect market efficiency to vary over time due to changes at the macro level. The oil market is particularly sensitive to the state of the global economy and some of the results could be related to major financial market events over the sample period. Lim and Brooks (2011), for example, refer to several studies documenting higher inefficiency in global stock markets during financial crises compared to pre- and post crises periods. Although the evidence in our empirical analyses is not entirely clear, we observe some indications of increased inefficiency during major oil price drops (e.g., 2008, 2015, and 2020).

However, as we focus on the highest (one minute) frequency in these rolling estimations, we must bear in mind that the rapid development of information technology for trading purposes is also likely to explain much of the results. In phases where investors start using innovative tools and techniques, new profit opportunities at higher and higher frequencies may be created. These arbitrage opportunities require costly investments, but they will be compensated, at least for some time (Grossman & Stiglitz, 1980). Once the new trading technology becomes "standard" and affordable to the average investor, however, the arbitrage opportunities should disappear or occur at other (likely higher) sampling frequencies. Hence, relating the development in market efficiency at the one-minute sampling to external economic conditions and major market events is difficult without also doing an in-depth analysis of the development in information technology and high-frequency trading.

The observed market inefficiencies in the current work are aligned to findings in Ewald et al. (2024) who observe intrad-day seasonal patterns in crude oil futures prices and demonstrate that these patterns can be exploited to create suitable long-short strategies which obtain positive alpha's in the CAPM sense. Further, the performance of these strategies increases specifically from 2015, reflecting an increase in market inefficiency during that period.

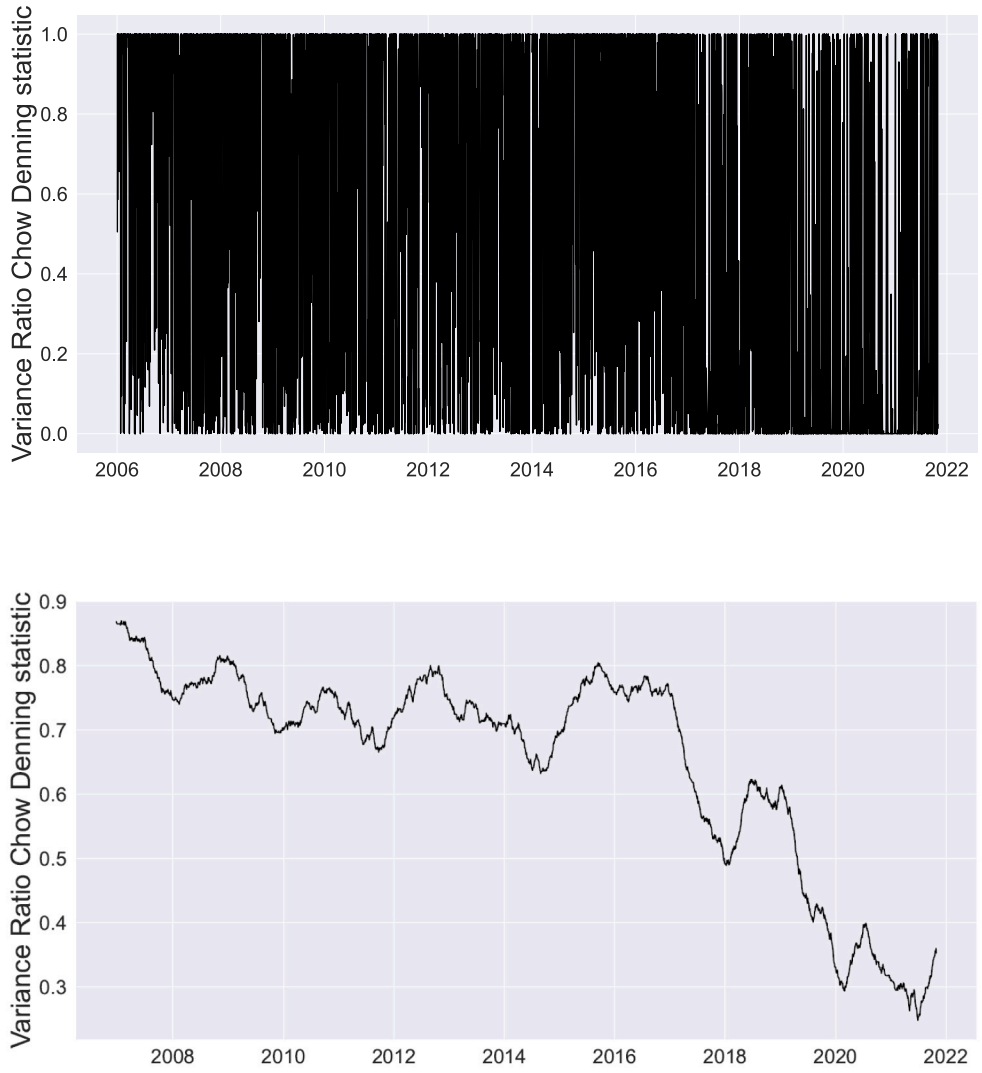

Fig. 6. Daily Variance Ratio test calculated using a one-minute sampling frequency (upper panel) and corresponding 252-days rolling average (lower panel).

5. Summary, implications, and directions for future research

In this paper, we have examined the weak-form market efficiency of the world's most heavily traded commodity, Brent Crude oil, across intra-daily sampling frequency. We have also examined how efficiency at the highest sampling frequency (one minute) has developed over time.

The empirical results of market efficiency across intra-daily sampling frequency are clear. The Brent Crude oil market is, on average, more inefficient at higher sampling frequencies (between one and 10 min) compared with lower sampling frequencies (more than 10 min) at the intra-daily level. We also document an exponential-like behavior in the market efficiency measures across sampling frequency, with the biggest changes occurring between one and 10 min. These findings hold across all four efficiency measures used.

We then focus particularly on the one-minute sampling frequency over time and find somewhat mixed results for the various efficiency measures. The results for the Hurst exponent and the Runs test suggest a close-to-efficient market over time, while the results for the VR test and the AMIM indicate inefficiency and even that the inefficiency has increased over time.

Inefficiencies in the Brent crude oil futures market at the intra-daily level can have important implications for market participants. For traders, the observed inefficiency may lead to arbitrage opportunities by implementing trading rules at high sampling frequencies (see e.g., Gatev et al. (2006)). Hence, investing in new technology that can exploit inefficiency may pay off, at least for some time. It is important to note, however, that we have not formally examined where the inefficiency stems from — only that it is present using statistical tests. Future research should, therefore, examine the nature of the inefficiency and whether it is possible to exploit it in trading to achieve abnormal returns. In that regard, one could also explore whether undertaking investments at very high trading frequencies could be sufficiently compensated when including transaction costs. So-called algorithmic trading has gained popularity over the last decade and the results of the present study may help explain why.

The results also have implications for risk managers as most risk models and hedging strategies assume efficient markets. The arbitrage opportunities can skew risk profiles for some time and risk managers may then struggle with safeguarding their positions if normal market dynamics are distorted. Such inefficiencies may also impact price stability and execution costs.

The main findings of the current study could also serve as a starting point for future research. First, we have not included transaction costs in our analyses. While transaction costs may have profound implications for market efficiency by influencing participation rates, affecting pricing mechanisms, and altering strategic behaviors, their aggregate effect on market efficiency is not fully understood. Liu (2004), for example, demonstrates that transaction costs can significantly reduce

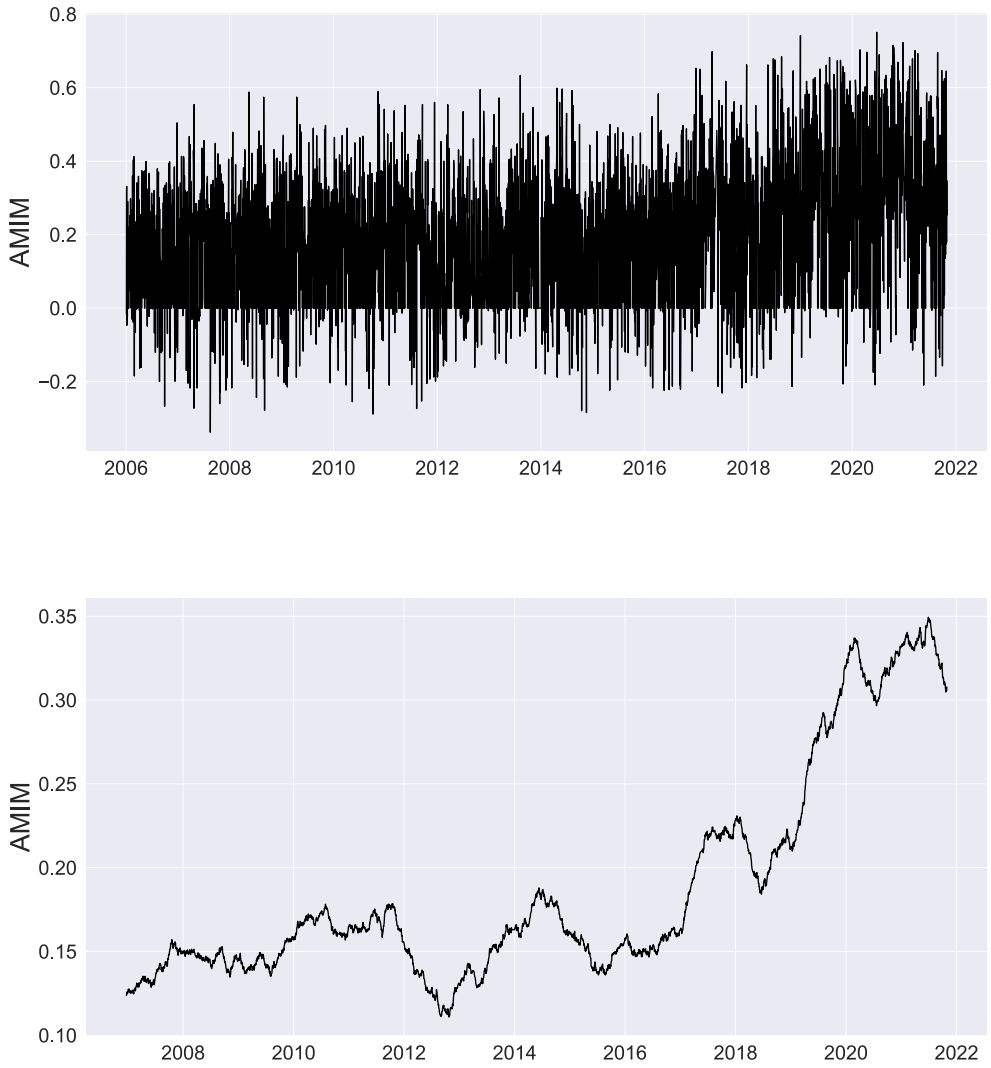

Fig. 7. Daily AMIM calculated using a one-minute sampling frequency (upper panel), corresponding 252-days rolling average (central panel) and the corresponding 252-day expanding window average (lower panel).

trading volume and diminish the predictability of stock returns. Šperka and Spišák (2013) argue that transaction costs, while often viewed negatively, can stabilize financial markets under certain conditions by influencing trading behavior and speculation patterns. They suggest that increased transaction costs might lead to more careful decision-making among agents, potentially aligning prices more closely with intrinsic values. For Brent Crude oil futures (Ewald et al., 2024) show that inefficiencies remain at high frequencies, even if transaction costs are accounted for. They also show that some of the inefficiency stem from intra-daily seasonality in oil price returns. Future studies should, therefore, explore the arbitrage opportunities more formally when accounting for costs associated with trading across various intra-daily trading frequencies, including the so-called ultra-high frequencies and algorithmic trading. Studying how efficiency varies between daytime and nighttime trading could also yield interesting results in that regard.

Second, we have examined market (in)efficiency using only statistical measures examining the intra-daily returns. Future studies could scrutinize the "origin" of the inefficiency by, for example studying the relationship between intra-daily seasonality in returns, volatility, liquidity, and the associated risk premia, and in this way expand the study by Ewald et al. (2024). One could also perform a more detailed analysis on the impact of major market events such as financial crises or geopolitical developments. Such a detailed examination of how specific events affect market efficiency could provide a deeper understanding of the market dynamics.

Third, more and more of the trading in Brent Crude oil futures takes place at higher frequencies. By going beyond the one-minute sampling frequency and focusing on sampling frequencies such as 30 s, 15 s, 5 s, 1 s, or even tick-by-tick data, a wealth of research opportunities within the topic of market efficiency for Brent Crude oil emerge.

Appendix. 95% confidence interval values

See Table A.1.

Table A.1
95% confidence interval values for various lags of the AR(q) model.

Lags	95% CI	Lags	95% CI	Lags	95% CI	Lags	95% CI	Lags	95% CI
1	0.6619	11	0.9244	21	0.9556	31	0.9682	41	0.9752
2	0.7605	12	0.9294	22	0.9573	32	0.9691	42	0.9757
3	0.8111	13	0.9338	23	0.9588	33	0.9699	43	0.9762
4	0.8424	14	0.9376	24	0.9603	34	0.9707	44	0.9767
5	0.8643	15	0.9411	25	0.9617	35	0.9714	45	0.9771
6	0.8806	16	0.9442	26	0.9629	36	0.9721		
7	0.8932	17	0.9469	27	0.9641	37	0.9728		
8	0.9033	18	0.9493	28	0.9652	38	0.9734		
9	0.9116	19	0.9516	29	0.9663	39	0.9740		
10	0.9185	20	0.9537	30	0.9673	40	0.9746		

Data availability

No.

References

Aït-Sahalia, Y., & Saglam, M. (2013). *High frequency traders: Taking advantage of speed*: *Technical report*, National Bureau of Economic Research.

Ait-Sahalia, Y., & Yu, J. (2008). *High frequency market microstructure noise estimates and liquidity measures*: *Technical report*, National Bureau of Economic Research.

Aloui, R., Gupta, R., & Miller, S. M. (2016). Uncertainty and crude oil returns. *Energy Economics*, *55*, 92–100.

Alvarez-Ramirez, J., Cisneros, M., Ibarra-Valdez, C., & Soriano, A. (2002). Multifractal hurst analysis of crude oil prices. *Physica A. Statistical Mechanics and its Applications*, *313*(3), 651–670.

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*, *39*(4), 885–905.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (1999). *(Understanding, optimizing, using and forecasting) realized volatility and correlation*: *Working Paper*.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica*, *71*(2), 579–625.

Arshad, S., Rizvi, S. A. R., Haroon, O., Mehmood, F., & Gong, Q. (2021). Are oil prices efficient? *Economic Modelling*, *96*, 362–370.

Bandi, F. M., & Russell, J. R. (2006). Separating microstructure noise from volatility. *Journal of Financial Economics*, *79*(3), 655–692.

Bariviera, A. F. (2017). The inefficiency of bitcoin revisited: A dynamic approach. *Economics Letters*, *161*, 1–4.

Barunik, J., & Kristoufek, L. (2010). On hurst exponent estimation under heavy-tailed distributions. *Physica A. Statistical Mechanics and its Applications*, *389*(18), 3844–3855.

Branch, B. S., & Ma, A. J. (2012). Overnight return, the invisible hand behind intraday returns? *Journal of Applied Finance (Formerly Financial Practice and Education)*, *22*(2).

Chakrabarty, B., Moulton, P. C., & Wang, X. F. (2022). Attention: How high-frequency trading improves price efficiency following earnings announcements. *Journal of Financial Markets*, *57*, Article 100690.

Charles, A., & Darné, O. (2009). The efficiency of the crude oil markets: Evidence from variance ratio tests. *Energy Policy*, *37*(11), 4267–4272.

Charles, A., Darné, O., & Kim, J. H. (2015). Will precious metals shine? A market efficiency perspective. *International Review of Financial Analysis*, *41*, 284–291.

Clinet, S., & Potiron, Y. (2021). Disentangling sources of high frequency market microstructure noise. *Journal of Business & Economic Statistics*, *39*(1), 18–39.

Dacorogna, M., Gençay, R., Muller, U., Pictet, O., & Olsen, R. (2001). *An introduction to high-frequency finance*. California, USA: Academic Press.

Ewald, C., Hadina, J., Haugom, E., Lien, G., Størdal, S., & Yahya, M. (2023). Sample frequency robustness and accuracy in forecasting Value-at-Risk for Brent Crude Oil futures. *Finance Research Letters*, *58*, Article 103916.

Ewald, C. O., Haugom, E., Ouyang, R., Smith-Meyer, E., & Størdal, S. (2024). Intra-day seasonality and abnormal returns in the brent crude oil futures market. *SSRN Electronic Journal*, URL https://ssrn.com/abstract=5037563.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417.

Fleming, J., Kirby, C., & Ostdiek, B. (2003). The economic value of volatility timing using "realized" volatility. *Journal of Financial Economics*, *67*(3), 473–509.

Ftiti, Z., Jawadi, F., Louhichi, W., & Madani, M. E. A. (2021). Are oil and gas futures markets efficient? A multifractal analysis. *Applied Economics*, *53*(2), 164–184.

Gale, D., & Yorulmazer, T. (2013). Liquidity hoarding. *Theoretical Economics*, *8*(2), 291–324.

Gately, D., Kyle, J. F., & Fischer, D. (1977). Strategies for OPEC's pricing decisions. *European Economic Review*, *10*(2), 209–230.

Gatev, E., Goetzmann, W. N., & Rouwenhorst, K. G. (2006). Pairs trading: Performance of a relative-value arbitrage rule. *The Review of Financial Studies*, *19*(3), 797–827.

Ghazani, M. M., & Ebrahimi, S. B. (2019). Testing the adaptive market hypothesis as an evolutionary perspective on market efficiency: Evidence from the crude oil prices. *Finance Research Letters*, *30*, 60–68.

Green, S. L., & Mork, K. A. (1991). Toward efficiency in the crude-oil market. *Journal of Applied Econometrics*, *6*(1), 45–66.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American Economic Review*, *70*(3), 393–408.

Hansen, P. R., & Lunde, A. (2005). A realized variance for the whole day based on intermittent high-frequency data. *Journal of Financial Econometrics*, *3*(4), 525–554.

Hansen, P. R., & Lunde, A. (2006). Realized variance and market microstructure noise. *Journal of Business & Economic Statistics*, *24*(2), 127–160.

Haugom, E. (2011). Some stylized facts about high-frequency nord pool forward electricity prices. *The Journal of Energy Markets*, *5*(1), 21–49.

Haugom, E., & Ullrich, C. J. (2012). Market efficiency and risk premia in short-term forward prices. *Energy Economics*, *34*(6), 1931–1941.

Haugom, E., Veka, S., Lien, G., & Westgaard, S. (2014). Estimating and evaluating value-at-risk forecasts based on realized variance: empirical evidence from ICE Brent Crude oil futures. *OPEC Energy Review*, *38*(4), 373–397.

Hurst, H. E. (1951). Long-term storage capacity of reservoirs. *Transactions of the American Society of Civil Engineers*, *116*, 770–808.

ICE (2023). Brent crude futures - Contract specifications. available at https://www.theice.com/products/{219}/Brent-Crude-Futures.

Kim, J. H., & Shamsuddin, A. (2008). Are Asian stock markets efficient? Evidence from new multiple variance ratio tests. *Journal of Empirical Finance*, *15*(3), 518–532.

Lee, S. S., & Mykland, P. A. (2012). Jumps in equilibrium prices and market microstructure noise. *Journal of Econometrics*, *168*(2), 396–406.

Lim, K.-P., & Brooks, R. (2011). The evolution of stock market efficiency over time: A survey of the empirical literature. *Journal of Economic Surveys*, *25*(1), 69–108.

Lim, K.-P., Brooks, R. D., & Kim, J. H. (2008). Financial crisis and stock market efficiency: Empirical evidence from Asian countries. *International Review of Financial Analysis*, *17*(3), 571–591.

Liu, H. (2004). Optimal consumption and investment with transaction costs and multiple risky assets. *The Journal of Finance*, *59*(1), 289–338.

Lo, A. W., & MacKinlay, A. C. (1988). Stock market prices do not follow random walks: Evidence from a simple specification test. *The Review of Financial Studies*, *1*(1), 41–66.

Mandelbrot, B. (1971). Analysis of long-run dependence in economics-r/s technique. *Econometrica*, *39*(4), 68++.

Martens, M., & van Dijk, D. (2007). Measuring volatility with the realized range. *Journal of Econometrics*, *138*(1), 181–207, 50th Anniversary Econometric Institute.

Okoroafor, U. C., & Leirvik, T. (2022). Time varying market efficiency in the brent and WTI crude market. *Finance Research Letters*, *45*, Article 102191.

Park, J. S., & Newaz, M. K. (2023). Time-series predictability for sector investing. *Financial Analysts Journal*, *79*(3), 136–154.

Patton, A. J., & Sheppard, K. (2015). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Review of Economics and Statistics*, *97*(3), 683–697.

Sabuhoro, J. B., & Larue, B. (1997). The market efficiency hypothesis: the case of coffee and cocoa futures. *Agricultural Economics*, *16*(3), 171–184.

Sadorsky, P. (2006). Modeling and forecasting petroleum futures volatility. *Energy Economics*, *28*(4), 467–488.

Serletis, A., & Andreadis, I. (2004). Random fractal structures in North American energy markets. *Energy Economics*, *26*(3), 389–399.

Shynkevich, A. (2025). Wine market efficiency: Is glass half full or half empty? *International Review of Economics & Finance*, *98*, Article 103895.

Sim, N., & Zhou, H. (2015). Oil prices, US stock return, and the dependence between their quantiles. *Journal of Banking & Finance*, *55*, 1–8, Global Governance and Financial Stability.

Šperka, R., & Spišák, M. (2013). Transaction costs influence on the stability of financial market: agent-based simulation. *Journal of Business Economics and Management*, *14*(sup1), S1–S12.

Tabak, B. M., & Cajueiro, D. O. (2007). Are the crude oil markets becoming weakly efficient over time? A test for time-varying long-range dependence in prices and volatility. *Energy Economics*, *29*(1), 28–36.

Tran, V. L., & Leirvik, T. (2019). A simple but powerful measure of market efficiency. *Finance Research Letters*, *29*, 141–151.

Wald, A., & Wolfowitz, J. (1940). On a test whether two samples are from the same population. *The Annals of Mathematical Statistics*, *11*(2), 147–162.

Wan, D., & Yang, X. (2017). High-frequency positive feedback trading and market quality: evidence from China's stock market. *International Review of Finance*, *17*(4), 493–523.

Wang, F., & Gacesa, M. (2023). Semi-strong efficient market of bitcoin and Twitter: An analysis of semantic vector spaces of extracted keywords and light gradient boosting machine models. *International Review of Financial Analysis*, *88*, Article 102692.

Wang, Y., Wei, Y., Wu, C., & Yin, L. (2018). Oil and the short-term predictability of stock return volatility. *Journal of Empirical Finance*, *47*, 90–104.

Weron, R. (2002). Estimating long-range dependence: finite sample properties and confidence intervals. *Physica A. Statistical Mechanics and its Applications*, *312*(1), 285–299.

Xu, L., Xue, M., Zhang, X., & Zhao, Y. (2023). Heterogeneously informed trading and the stock market efficiency during the COVID-19 pandemic. *International Review of Financial Analysis*, *87*, Article 102608.

Yan, S., Ling, X., Cao, T., Hu, S., Xiong, R., Ye, H., & Zhang, R. (2022). Algorithmic trading and challenges on retail investors in emerging markets. *Journal of Economics, Finance and Accounting Studies*, *4*(3), 36–41.

Yang, J., Li, Z., & Wang, T. (2021). Price discovery in Chinese agricultural futures markets: a comprehensive look. *Journal of Futures Markets*, *41*(4), 536–555.

Yu, Z., Yang, J., & Webb, R. I. (2023). Price discovery in China's crude oil futures markets: An emerging Asian benchmark? *Journal of Futures Markets*, *43*(3), 297–324.

Yuferova, D. (2024). Algorithmic trading and market efficiency around the introduction of the NYSE Hybrid Market. *Journal of Financial Markets*, *69*, Article 100909.

Zhang, H., Qian, S., & Ma, Z. (2024). An analysis of the market efficiency of the Chinese copper futures based on intertemporal and intermarket arbitrages. *International Review of Financial Analysis*, *94*, Article 103243.