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Liquidity and Market Efficiency in Borsa Istanbul

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Abstract

The Borsa Istanbul has experienced a significant increase in investor participation in the past few years, and the growing number of companies are opting to raise capital through IPOs (Initial Public Offerings). In the context of this transformation, the goal of this research is to investigate the connection between the market efficiency and liquidity of 397 stocks traded on Borsa Istanbul by using the daily data over the period from 1 January 2022 to 18 August 2023, including the new stocks that have been listed in recent years. The stocks are ranked in accordance with the degree of informational efficiency using a sample entropy (SampEn) approach. The analysis shows that all stocks exhibit different levels of informational complexity and illiquidity, and many stocks display evidence of autocorrelation and non-independence. Further, it is revealed that entropy and liquidity have a significant relationship on a cross-sectional basis, suggesting that liquidity has an important impact on both inefficiency and predictability.

Keywords: *Market efficiency, Liquidity, Borsa Istanbul, Entropy.*

Borsa İstanbul'da Likidite ve Piyasa Etkinliği

Öz

Borsa İstanbul, yatırımcı katılımında önemli bir artış göstermekte olup şirketler de halka arz yoluyla sermaye arttırımına gitmektedir. Bu bağlamda çalışmanın amacı, son yıllarda Borsa İstanbul'a yeni kote olan hisse senetleri de dahil olmak üzere 397 şirketin hisse senetlerinin piyasa etkinliği ve likiditesi arasındaki ilişkiyi araştırmaktır. 1 Ocak 2022 – 18 Ağustos 2023 dönemi günlük verilerin kullanıldığı çalışmada, hisse senetlerini bilgi etkinliği düzeylerine göre sıralamak için sample entropi yöntemi kullanılmıştır. Elde edilen bulgulara göre, tüm hisse senetleri farklı seviyelerde bilgi karmaşıklığı ve likidite eksikliği sergilemekte olup çalışmada, birçok hisse senedi getirilerinin otokorelasyon gösterdiği ve bağımsız olmadığına dair kanıtlar da elde edilmiştir. Ayrıca, entropi ve likiditenin yatay kesit bazında anlamlı bir ilişkiye sahip olduğu ve likiditenin hem etkinlik hem de tahmin edilebilirlik üzerinde önemli bir rol oynadığı ortaya konmuştur.

Anahtar Kelimeler: *Piyasa etkinliği, Likidite, Borsa İstanbul, Entrop*

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INTRODUCTION

The Borsa Istanbul has experienced a remarkable transformation in recent years, witnessing an astonishing surge in investor participation. As of the end of June 2023, the overall number of investors reached 4.4 million with an increase of 1 million 972 thousand people in comparison to the same time of the last year, marking an extraordinary 81% increase within this short timeframe. This surge in investor activity coincides with a record number of Initial Public Offerings (IPOs) on the exchange, effectively attracting a wave of new market participants. While the number of companies traded on BIST ALL was 444 as of the end of 2022, this number increased to 468 after 24 IPOs in the first half of 2023 (Turkish Investor Relations Society [TUYID], 2023).

In this constantly shifting environment, understanding the efficiency of stocks across the entire spectrum is crucial for investors, analysts, and policymakers. The efficient market hypothesis (EMH) claims that all historical market prices have been entirely captured in securities prices in its weak form (Fama, 1970). In this regard, it is not possible to outperform the market by utilizing investment techniques that rely on historical securities prices. Efficient markets are important for ensuring fair pricing, capital allocation, and overall stability in the financial system.

The present research investigates the connection between the informational efficiency and liquidity across a wide range of stocks traded on the Borsa Istanbul. Liquidity is commonly described as the capability to trade big amounts at minimal costs and without affecting the price (Pástor & Stambaugh 2003: 644). Briefly, liquidity is the ability of an asset to be converted into cash without losing its value. Liu (2006) highlights four aspects of liquidity: trading cost, trading quantity, trading speed and price impact. The first dimension encompasses all costs associated with the trade of a security. In the second dimension, it indicates how much a security can be transacted at a specified expense. The third dimension is the speed at which a security can be exchanged for a specific amount and price. The last dimension is how easily a given quantity of a security can be traded with minimal impact on the price. In the literature, a wide range of measures are presented and used to estimate the liquidity on the stock market. Despite concentrating on distinct features of liquidity, these measures are closely related (Le & Gregoriou, 2020).

Market efficiency and liquidity are closely related and essential elements of stock markets. High liquidity promotes effective trading mechanisms that allow prices to respond quickly to new information and allow for a fair valuation of assets because of higher trade volume and participant involvement. On the other hand, illiquid markets may experience slower price adjustments, potentially leading to inefficiencies (Wei, 2018). Informed traders have a significant impact on prices through their trading activity, pushing prices up when they buy and down when they sell. Their trades, which are based on estimates of fundamental value, drive prices towards these estimates, so that prices reflect their perceptions of fundamental value. Therefore, when informed traders accurately estimate values, their trading improves the informativeness of prices. However, the effectiveness of informed trading and the informativeness of prices depend on the accessibility of information and the level of market liquidity. In markets with limited liquidity and high information acquisition costs, prices may not be very informative, thereby hampering market efficiency (Harris, 2003, pp. 222-244).

The informational efficiency of the Turkish stock market has been analyzed by a growing number of studies. Among these previous investigations, several studies documented a lack of compelling support for the EMH (Bal et al., 2021; Bektur & Aydın, 2019; Duman Atan et al., 2009; Gözbaşı, 2014; Karademir & Evci, 2020; Yücel, 2016; Zeren et al., 2013), while others report that stock prices behave according to the theory (Ayaydın et al., 2018; Aytekin, 2021; Çevik & Erdoğan, 2009; Çevik, 2012; Malcıoğlu & Aydın, 2016; Şahin, 2020; Tanrıöver & Çöllü, 2015).

While many studies have looked into how efficient the Turkish stock market is, there hasn't been much research on how market efficiency relates to liquidity. As far as we know, this connection hasn't been thoroughly investigated in previous studies. The sample entropy approach is used to assess market efficiency and the Amihud illiquidity measure is selected for this study due to its reliability and ease of use in measuring liquidity. It involves only daily trade data, making it simple to compute and compare market instruments, particularly in situations when market microstructure information is unavailable (Amihud, 2002).

This article differs from the body of prior research on the weak-form efficiency of the Turkish stock market efficiency in two ways. Firstly, considering the amount of new stocks that have been listed in over the past few years, the data set is current and has not been examined in earlier studies on the Turkish stock market. Secondly, this research explores the impact of liquidity on the informational efficiency of the Turkish stock market by constructing a hierarchy of stocks based on their entropy level from the lowest to the highest.

The rest of this paper is organized as follows: Section 1 summarizes the literature. Section 2 presents the methodology used in this study. In Section 3, the data used in this work is presented. Section 4 presents the empirical results. Finally, Section 5 provides a summary and conclusion for the paper.

1. LITERATURE REVİEW

The literature examines the relationship between market efficiency and liquidity in different financial markets, using different methodologies and empirical evidence. Cajueiro and Tabak (2004) examine long-term memory dependence in Asian stock markets and find that liquidity and market restrictions affect market efficiency differently across regions. Bariviera (2011) extends this analysis to the Thai stock market, using proxies for liquidity, and finds a weak correlation between liquidity and efficiency measures. Okoroafor and Leirvik (2022) focus on the crude oil market, highlighting the importance of liquidity for market efficiency during crises. They find a significant positive relationship between illiquidity and inefficiency in both the Brent and WTI crude oil markets, especially during financial crises. Ibikunle et al. (2016) also highlight the link between liquidity and efficiency, focusing on the carbon exchange market. In addition, Sensoy (2019) and Takaishi and Adachi (2020) analyse bitcoin markets and show how liquidity affects market efficiency over time. Hansen and Halvorsen (2023) extend this analysis to ETFs during crises and find a correlation between efficiency and liquidity in G7 countries. Chordia et al. (2008) examine the relationship between market liquidity and efficiency in the NYSE and find that liquidity enhances market efficiency through improved order flow matching and arbitrage activity. Finally, Young and Auret (2018) explore the interplay between market structure, liquidity, and efficiency, highlighting the importance of liquidity in facilitating price discovery and convergence to market efficiency. Overall, the literature emphasizes the complex relationship between liquidity and market efficiency, underscoring their interdependence and influence on financial market dynamics.

2. METHODOLOGY

2.1. Liquidity Measure

The Amihud illiquidity measure is formulated as follows:

$$ILLIQ_{iT} = \frac{1}{D_T}\sum_{t=1}^{D_T}\frac{|R_{it}|}{P_{it}VOL_{it}} \quad (1)$$

where D_T represents the number of trading days in the sample period, R_{it} indicates the daily return of stock i on day t in TL, VOL_{it} denotes the daily volume of stock i on day t traded, and P_{it} describes the daily price of stock i on day t in TL (Amihud,2002). This metric can be used as a crude proxy for the price impact of daily aggregate trades and sheds light on the link between volume and price change. In our analysis, it is used after being multiplied by 10^9.

2.2. Sample Entropy

Sample entropy (SampEn) is an information-theoretical concept for quantifying the degree of regularity and predictability in time-series data. The method, developed by Richman and Moorman (2000), was originally used to analyze the short and noisy signals encountered in biomedicine. SampEn analysis produces a non-negative number for a time series. A score of higher values indicates more apparent randomness or serial disorder in the process, while a score of lower values means more clearly noticeable features or patterns. In other words, a time series with a lot of repeating patterns has a low SampEn score; on the other hand, processes that are more complex and therefore less predictable have a higher value. The entropy-based method has been used in many markets as a gauge of market efficiency and offers further insight by determining the degree of informational efficiency (Alkan, 2023; Alvarez-Ramirez et al., 2012; Oh et al., 2007; Ortiz-Cruz et al., 2012; Süsay Alkan, 2024; Wang & Wang, 2021; Wang et al., 2012).

Let *m* represent the embedding dimension of two segments in a sequence to be compared, and let *r* denote the similarity threshold for accepting matches. To compute sample entropy for a time series $\boldsymbol{x} = \{x_1, x_2, ..., x_N\}$ consisting of *N* points, the following steps should be followed (Chou, 2014; Richman & Moorman, 2000):

Step 1. Form m-dimensional template vectors $x_m(i)$, a sequence of vectors from 1 to N-m+1

$$x_m(i) = \{x_{i+k}: 0 \leq k \leq m-1\}, \;\; 1 \leq i \leq N-m+1$$

Step 2. For each $x_m(i)$, the distance between two such vectors $x_m(i)$ and $x_m(j)$ is computed by employing the Chebyshev distance:

$$d(x_m(i), x_m(j)) = \left||x_m(i), x_m(j)|\right| = max\{\left|x_{i+k} - x_{j+k}\right|: 0 \leq k \leq m-1\}, 1 \leq i, j \leq N-m+1, j \neq i$$

Step 3. Given the threshold parameter r, let $n_i^m(r)$ represent the number of matches for $x_m(i)$ within a distance r. $C_i^m(r)$ is expressed as follows:

$$C_i^m(r) = \frac{n_i^m(r)}{N-m} \quad (2)$$

Step 4. Compute

$$C^m(r) = \frac{\sum_{i=1}^{N-m+1} C_i^m(r)}{N-m+1} \quad (3)$$

Step 5. Raise the dimension from m to m+1, then replicate the above procedure to get $C^{m+1}(r)$.

Step 6. Sample entropy is computed as:

$$SampEn(m, r, N) = -ln\frac{C^{m+1}(r)}{C^m(r)} \quad (4)$$

2.3. Relative Informational Efficiency Index

According to the EMH, a weakly efficient market should have stock prices that are random walks and returns that are Gaussian white noise. As a result, the entropy of Gaussian white noise is used as a theoretical criterion to measure the efficiency of stock returns. For each stock, relative informational efficiency index is defined as follows according to (Ortiz-Cruz et al., 2012):

$$I_{IME} = \frac{SampEn(m, r)}{\beta} x100\% \quad (5)$$

where β represents the upper limit for Gaussian white noise entropy derived from 10,000 Monte Carlo simulation instances. Stock efficiency is only fractional if the entropy of stock return is below that of Gaussian white noise, or $I_{IME} < 100\%$.

In accordance with previous studies (Richman & Moorman, 2000; Wang, et al., 2012), the embedding dimension (m) is set to 2, and the tolerance range (r) is set to 0.25 times the standard deviation (σ) of the return series in this study. Similar to Wang et al. (2012), the returns are normalized by dividing by their standard deviations, and then the sample entropy is computed.

3. DATA

The dataset used for this study is comprised of historically daily closing prices of 397 stocks registered on the Borsa Istanbul. We consider only stocks traded from 1 January 2022 to 18 August 2023 with full price and volume data. The sample period covers 406 trading days. All the dataset used in this research is taken from Finnet. The daily closing prices are transformed to logarithmic returns for each stock as follows:

$$R_i(t) = \log P_i(t) - \log P_i(t-1) \quad (6)$$

where $R_i(t)$ denotes the logarithmic return of i-th stock at time t, and P_i represents the closing price of the i-th stock at day t and t-1, respectively. Table 1 contains the tickers for these equities. They are classified according to the degree of illiquidity, which is described in the methodology section.

Table 1: Classification of Stocks Based on Amihud Illiquidity Ratio.

Category 1		Category 2		Category 3		Category 4		Category 5	
AEFES	KONTR	ADESE	ISSEN	AKENR	KUYAS	ACSEL	KNFRT	ADEL	INGRM
AKBNK	KORDS	AFYON	JANTS	AKSGY	KZBGY	AGESA	KRONT	AKMGY	INTEM
AKSA	KOZAA	AGHOL	KAREL	AKSUE	MAKTK	AGYO	KRSTL	ALMAD	IZFAS
AKSEN	KOZAL	AKFGY	KARTN	ALCAR	MANAS	AKCNS	KRTEK	ATAGY	IZINV
ALARK	KRDMA	AKGRT	KATMR	ALCTL	MARTI	AKYHO	LKMNH	ATEKS	KAPLM
ARCLK	KRDMD	ALBRK	KERVT	ALKA	MEGAP	ANSGR	MAALT	AVGYO	KGYO
ASELS	MAVI	ALGYO	KLGYO	ANELE	METRO	ARENA	MEDTR	AVTUR	KIMMR
AYDEM	MGROS	ALKIM	KLKIM	ANHYT	MNDRS	ARZUM	MERCN	AYCES	KRGYO
BASGZ	ODAS	ANGEN	KONKA	ARASE	MNDTR	ATATP	MERIT	BAKAB	LIDFA
BERA	OTKAR	ARDYZ	KONYA	BFREN	MRGYO	AVHOL	MERKO	BANVT	LINK
BIMAS	OYAKC	ASUZU	KRDMB	BIZIM	NETAS	BEYAZ	MIPAZ	BAYRK	LUKSK
CCOLA	PETKM	AVOD	KRVGD	BMSCH	NIBAS	BOSSA	MSGYO	BRKSN	MEPET
CIMSA	PGSUS	AYEN	KTSKR	BNTAS	NUGYO	CEOEM	MTRKS	BURCE	METUR
DOAS	PSGYO	AYGAZ	LOGO	BSOKE	ORGE	CMBTN	NUHCM	BURVA	MRSHL
DOHOL	SAHOL	BAGFS	MAGEN	BTCIM	OSTIM	CRDFA	ORCAY	CELHA	MZHLD
ECILC	SASA	BIOEN	MIATK	CRFSA	OZGYO	CUSAN	OYYAT	COSMO	OSMEN
EGEEN	SELEC	BJKAS	MOBTL	DGNMO	PAPIL	DAGI	PAMEL	DAGHL	OYLUM
EKGYO	SISE	BOBET	MPARK	DOCO	PCILT	DERHL	PEGYO	DENGE	OZRDN
ENJSA	SKBNK	BRISA	NATEN	DYOBY	PENTA	DERIM	PETUN	DESA	PAGYO
ENKAI	SNGYO	BRLSM	NTGAZ	EGGUB	PNSUT	DMSAS	PINSU	DESPC	PKART
EREGL	SOKM	BRSAN	NTHOL	EGPRO	PRKME	DZGYO	PKENT	DGATE	POLTK
FENER	TAVHL	BRYAT	OZKGY	EGSER	RTALB	EMKEL	RNPOL	DGGYO	PRZMA
FROTO	TCELL	BUCIM	PARSN	ELITE	RYGYO	EPLAS	RYSAS	DITAS	PSDTC
GARAN	THYAO	CANTE	PEKGY	FADE	SARKY	ERSU	SAFKR	DNISI	RAYSG
GENIL	TKFEN	CEMAS	PENGD	FLAP	SAYAS	ESCAR	SAMAT	DOBUR	RODRG
GESAN	TKNSA	CEMTS	POLHO	FMIZP	SRVGY	ESCOM	SANKO	DOGUB	SANEL
GLYHO	TOASO	CLEBI	PRKAB	FRIGO	TATGD	FONET	SEKFK	DOKTA	SANFM
GOZDE	TSKB	DARDL	QUAGR	GEREL	TEKTU	GEDIK	SELVA	DURDO	SEKUR
GSDHO	TSPOR	DEVA	RALYH	GLCVY	TRCAS	GEDZA	SEYKM	EDATA	SELGD
GSRAY	TTKOM	ECZYT	TEZOL	GOLTS	TSGYO	GENTS	SILVR	EDIP	SMART
GUBRF	TTRAK	ERBOS	TMSN	GSDDE	UNLU	GLRYH	SKTAS	EGEPO	SONME
GWIND	TUKAS	ESEN	TRGYO	IEYHO	VAKKO	GMTAS	TLMAN	ETILR	TETMT
HALKB	TUPRS	FORMT	TURSG	IHLAS	VBTYZ	HEDEF	TMPOL	EUHOL	TGSAS
HEKTS	ULKER	GOODY	USAK	IHLGM	VERUS	HUBVC	TUCLK	GARFA	TURGG

Category 1		Category 2		Category 3		Category 4		Category 5	
HLGYO	ULUUN	HDFGS	VAKFN	INFO	YESIL	HURGZ	TUREX	GLBMD	UFUK
IPEKE	VAKBN	INDES	VERTU	ISKPL	YKSLN	ICBCT	ULUFA	ICUGS	ULAS
ISCTR	VESBE	INVEO	VKGYO	ITTFH	YUNSA	IHEVA	YAPRK	IDEAS	ULUSE
IZMDC	VESTL	ISFIN	YATAS	KARYE	YYAPI	IHGZT	YAYLA	IDGYO	VANGD
KARSN	YKBNK	ISGYO	YEOTK	KLMSN		ISGSY	YGYO	IHAAS	VKING
KCHOL	ZOREN	ISMEN		KUTPO		KFEIN		IHYAY	YGGYO
									ZEDUR

Note: Using the Amihud illiquidity ratio, stocks are divided into five groups. The most liquid stocks in our sample are in Category 1, while the least liquid stocks are in Category 5.

4. RESULTS

Table 2 presents average descriptive statistics on the returns of our stocks classified by Amihud ratio, where Category 1 indicates the highest liquidity and Category 5 represents the lowest liquidity. In Borsa Istanbul, we do not see any indications of an illiquidity premium, which suggests that investors may not necessarily seek a higher return for holding illiquid assets. Liquidity premiums are the additional returns or yields that investors typically demand in exchange for investing in less liquid assets. Basically, it is the extra return investors expect to receive from holding an asset that is more difficult to convert into cash. Theoretically, investors demand extra returns on less liquid assets to offset the higher expenses of transacting these assets; consequently, the expected return decreases with asset liquidity.

By employing the bid-ask spread as a surrogate for liquidity, Amihud and Mendelson (1986) demonstrate that the cost of illiquidity (liquidity cost) has a positive relationship with expected asset returns. When turnover ratios and trading volumes are employed as indicators of liquidity, Brennan et al. (1998) reveal a negative relationship between liquidity and demanded returns on US equities. This association has been verified by Bekaert et al. (2007) in emerging markets and by Atilgan et al. (2016) in the context of Borsa Istanbul for the study period from January 2002 to December 2012. This paper has uncovered a number of intriguing results that disagree with past studies.

Our results are in line with recent research on cryptocurrencies, which also did not discover any indication of an illiquidity premium. Unlike traditional asset classes, Wei (2018) found that crypto-investors do not seem to require a return premium for holding illiquid assets. This is consistent with our finding that Borsa Istanbul does not exhibit signs of an illiquidity premium, indicating that investors may not necessarily seek higher returns for holding illiquid assets in this market. The similarity of the results across different asset classes underlines the robustness and the broader applicability of our findings, which highlights the unique dynamics of liquidity and market efficiency in different financial markets. Furthermore, we observe a low degree correlation between illiquidity and stock volatility, skewness, and kurtosis. It has been observed that when the illiquidity level rises, so do their values. A positive skewness may indicate that investors are more optimistic overall in the sample period.

Table 2: Descriptive Statistics of Stock Returns Sorted by Liquidity

Rank by liquidity	Category	Amihud	Mean	SD	Skewness	Kurtosis	Entropy
High Liquidity	1	0.13954	0.00341	0.03317	0.07511	4.11821	77.01675
	2	0.52148	0.00305	0.03357	0.13137	4.13757	74.70436
	3	1.05808	0.00264	0.03397	0.14129	4.27436	71.45995
	4	1.83175	0.00271	0.03487	0.15728	4.31098	69.50138
Low Liquidity	5	6.69407	0.00303	0.03771	0.28802	3.98821	66.23261

Table 2 shows that the average entropy value tends to rise in higher quintiles while displaying declines as liquidity levels fall, according to the general pattern. It is evident from this behavior that the predictability of stock prices appears to be fairly higher in the lowest quintiles, as the average entropy value is relatively small compared to the higher quintiles. According to Gulko (1999), the larger the number of price patterns (maximum entropy), the more difficult it is to anticipate the price's future direction. As a result, stocks with a low level of entropy are less complicated to forecast, as opposed to stocks with high entropy levels, which call for the use of more sophisticated prediction techniques and algorithms. Additionally, our analysis reveals that none of the stocks in our sample demonstrate full informational efficiency, as indicated by their calculated efficiency indices falling below 100%. This suggests that all stocks exhibit fractional efficiency, meaning they do not fully reflect all available information. In short, stocks with higher levels of liquidity are observed to be more complex than those with lower levels of liquidity, further highlighting the intricate relationship between liquidity and efficiency in financial markets.

We further tested our findings on relative information efficiency and liquidity levels using four statistical methods designed to assess market efficiency. First, the Ljung-Box test is used to investigate return autocorrelation (Ljung & Box, 1978). Second, the independence of the stock return is tested using the runs test (Wald & Wolfowitz, 1940) and the Bartels test (Bartels, 1982). Finally, the variance ratio test designed by Lo and MacKinlay (1988) is used to determine if the standard deviation of returns scales with T. Kim's (2009) wild-bootstrapped automatic variance test (AVR) is employed to perform the variance-ratio test. These specific tests are selected because of their ability to address different dimensions of market efficiency, including autocorrelation, randomness, and the scaling of volatility, which are central to our investigation of the relationship between relative information efficiency and liquidity levels. Additionally, these tests have been widely utilized in the finance literature and are well-established tools for assessing market efficiency.

The Table-3 summarizes the combined P values for the statistical tests across five categories of stocks ranked by liquidity, with asterisks denoting significance levels. Using Empirical Brown's Method (Poole et al., 2016), it shows that high liquidity groups (Categories 1-3) generally exhibit more random returns, with higher combined P values for the Runs and AVR tests. In contrast, low liquidity groups (Categories 4-5) show strong evidence of serial correlation and non-randomness, particularly in the Ljung–Box and Bartels tests, indicated by significantly low combined P values. This highlights the relationship between liquidity levels and the presence of randomness in stock returns.

Table 3: Combined P-Values for the Four Efficiency Tests

Rank by liquidity			Combined p-values			
	Category	**Amihud**	**Ljung–Box**	**Runs**	**AVR**	**Bartel**
High liquidity	1	0.14	0.050*	0.427	0.428	0.101
	2	0.521	0.028*	0.253	0.387	0.025*
	3	1.058	0.009**	0.338	0.581	0.024*
	4	1.832	0.001**	0.156	0.000**	0.007**
Low liquidity	5	6.694	0.000**	0.202	0.570	0.002**

Note: * and ** denote the significance levels at the 5% and 1%, respectively.

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Table 4: The Number of Stocks That Fail Each Test.

Rank by liquidity			Number of stocks			
	Category	**Amihud**	**Ljung–Box**	**Runs**	**AVR**	**Bartel**
High liquidity	1	0.14	18	1	3	18
	2	0.521	19	7	3	25
	3	1.058	24	4	0	25
	4	1.832	30	13	5	26
Low liquidity	5	6.694	37	11	2	32

According to their respective P values, the null hypothesis of randomness is rejected for 128 stocks in the Ljung-Box test, 36 stocks in the Runs test, 13 stocks in the AVR test, and 126 stocks in the Bartel test. The Table-4 presents the number of stocks failing various statistical tests across five categories of liquidity. It counts the number of stocks that have a P value less than 0.05 in each category. High liquidity categories (1-3) generally exhibit fewer stocks failing the Ljung–Box, Runs, and Bartels tests, indicating more randomness and less serial correlation in their returns. In contrast, low liquidity categories (4-5) show a higher number of stocks failing these tests, suggesting stronger evidence of serial correlation and deviations from randomness. The AVR test results are mixed, with significant failures in medium to low liquidity stocks. Overall, high liquidity stocks exhibit more randomness, while low liquidity stocks show significant serial correlation and deviations from randomness.

The findings align with earlier empirical research that has indicated a positive correlation between market efficiency and liquidity. Examples of such research include studies of the stock market (Bariviera, 2011; Cajueiro & Tabak, 2004), cryptocurrency market (Wei, 2018), carbon exchange market (Ibikunle et al., 2016), and crude oil spot market (Okoroafor & Leirvik, 2022). A liquid market makes it possible for market participants to take advantage of any arbitrage possibilities available to them, resulting in higher price efficiency. On the other hand, an illiquid market will leave investors unable to take advantage of mispricings, resulting in lower price efficiency. During the process of price discovery, frequent trading allows for the absorption of new information. In contrast, the absence of active traders will result in a longer period of time for market participants to respond to new information, which in turn will lead to an inefficient market.

5. CONCLUSION

This work investigates the relationship between the informational complexity and liquidity in the Turkish stock market. The sample entropy has been applied to assess the market efficiency of the 397 stocks by using the daily data for the period between 1 January 2022 and 18 August 2023. The analysis shows that all stocks show varying degrees of illiquidity and informational complexity, and that many show indications of non-independence and autocorrelation. The sample entropy approach is based on the principle that larger entropy levels imply a broader diversity of price change structures. Accordingly, a stock with a high entropy value is more complicated than one with a low entropy value. Results indicate that sample entropy and liquidity have a strong relationship. It has been shown that the average entropy values increase in higher liquidity quintiles, implying that high-liquidity stocks have greater efficiency. According to the findings, Borsa Istanbul does not display any evidence of an illiquidity premium, which implies that investors may not necessarily pursue a higher return for holding illiquid stocks.

Our study has limitations worth noting. Firstly, we use low-frequency data (daily returns), which may overlook intraday fluctuations and high-frequency trading activity, limiting the depth of our analysis. Secondly, we do not account for external factors like macroeconomic conditions or regulatory changes, potentially constraining the comprehensiveness of our findings. Future research should address these limitations for a more nuanced understanding of market efficiency and liquidity dynamics.

AUTHOR STATEMENT

Statement of Research and Publication Ethics

This study has been prepared in accordance with scientific research and publication ethics.

Author Contributions

The author carried out the work entirely alone.

Conflict of Interest

There is no conflict of interest for the authors or third parties arising from the study.

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