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The Relationship between Market Liquidity and Market Efficiency: A Detrended Cross-Correlation Analysis (DCCA) of Tehran Stock Exchange

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Highlights

- **The study aims to investigate the connection between efficiency and liquidity in the TSE over a specified period.**
- **The Market Efficiency Index (EI) is calculated using DFA on daily closing prices.**
- **Market Liquidity is proxied by the moving average of trading volume over a one-year period.**
- **The correlation between efficiency and liquidity varies over time, showing both positive and negative correlations in different periods.**

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Abstract

This study examines the dynamic relationship between market efficiency and liquidity in Tehran Stock Exchange (TSE) from March 2010 to March 2024. To achieve this, we employ the Detrended Cross-Correlation Analysis (DCCA) method using a one-year rolling window. Initially, we calculate the market efficiency index (EI) through the Detrended Fluctuation Analysis (DFA) applied to the time series of daily closing prices. Simultaneously, the moving average of daily trading volume over a one-year period is used as a proxy for market liquidity. The results indicate that the correlation between efficiency and liquidity fluctuates over time, exhibiting both positive and negative values in different periods. However, these variations remain weak, with correlation coefficients being close to zero for most time frames. This suggests that there is no clear or stable relationship between the two variables. Unlike previous studies that have suggested a significant role of liquidity in enhancing market efficiency, our findings do not support a strong link between trading volume and efficiency in the TSE. These results imply that market liquidity, as measured by trading volume, does not exhibit a strong or consistent relationship with market efficiency and vice versa. Accordingly, increasing trading volume and market liquidity does not necessarily translate into greater efficiency, and other influential factors must be considered to enhance market efficiency.

1. Introduction

Various theoretical arguments and empirical findings indicate a strong connection between market liquidity and the efficiency of financial markets. Considering the significant importance of both concepts in economic literature,

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their interrelationship has been and remains a highly debated issue. Consequently, it is reasonable to inquire whether fluctuations in liquidity are related to changes in the level of efficiency.

Liquidity is a main criterion of the stock market quality that should be considered by investors before performing stock analysis from both the technical and fundamental point of view (Chordia, et al, 2008; Utami et al., 2017). The more liquid the stock market, the more attractive it will be for investors to invest their money. The motivation for examining liquidity arises from the idea that investors evaluate investment opportunities in the stock market by weighing risk against potential returns, and liquidity risk is one of the most significant factors influencing their decisions.

Indeed, market liquidity plays a crucial role in ensuring the stability of financial system. A breakdown of the system, or the rise of systemic risk, can result from a loss of confidence among market participants in the price discovery mechanism (Muranaga & Shimizu, 1999). Given the significant costs associated with diminished market liquidity, the improvement of market liquidity is essential for those involved in the market.

Moreover, the level of informational efficiency is determined by the rate at which information is integrated into security prices and the extent to which prices accurately reflect that information (Fama, 1970).

In practice, factors related to market microstructure such as severe order imbalances in capital markets, the cognitive limitations of market makers, and market frictions, can lead to temporary deviations of prices from their arbitrage-free equilibrium value (Gilson & Kraakman, 1984). Meanwhile, illiquidity is identified as a potentially significant friction that hinders the restoration of market efficiency by influencing the aforementioned factors (Rösch et al., 2017). Understanding the connection between market liquidity and efficiency has significant implications for investors, policymakers, and market regulators. Efficient markets provide accurate signals for capital allocation, reduce information asymmetry, and contribute to economic growth. At the same time, liquidity risk is recognized as a critical factor in financial stability. During financial crises, sudden liquidity shortages can lead to increased price volatility and systemic risk. Therefore, a comprehensive examination of this relationship can aid in the development of more effective regulatory policies and risk management strategies.

Despite extensive research on this topic in developed and emerging markets, studies on developing markets, including Iran, remain limited. The Tehran Stock Exchange operates under unique institutional and macroeconomic conditions that may influence the connection between liquidity and market efficiency differently. Factors such as government interventions, exchange rate controls, currency fluctuations, and geopolitical risks create structural frictions that can affect liquidity dynamics and price efficiency.

Moreover, the Iranian stock market has experienced periods of extreme volatility, speculative bubbles, and liquidity shortages, highlighting the need for a deeper understanding of the mechanisms driving these fluctuations. Given that the Tehran Stock Exchange serves as one of the primary investment avenues in an economy with restricted access to foreign capital, maintaining market efficiency and ensuring sufficient liquidity are crucial for enhancing investor confidence and fostering sustainable financial development.

This study explores this issue by analyzing return and liquidity data for TSE stocks from 2010 to 2024. Various methodologies have been employed to investigate the connection between market Liquidity and Efficiency in stock markets. In this study, the DCCA framework, proposed by Podobnik & Stanley (2008), is utilized to examine correlation between the Efficiency Index and trading volume in Tehran Stock Exchange using daily data. Unlike conventional approaches, this method accounts for potential variations in both the magnitude and direction of correlation across different time horizons and scales.

The rest of this paper is structured as follows: In Section 2, a brief review of the relevant literature is presented, covering both theoretical aspects and previous studies. Section 3 describes the research data and methodology. The fourth section provides interpretation of the results derived from the model estimation, and conclusion is presented in the final section.

2. A Review of the Related Literature

This section review covers key concepts of market liquidity and market informational efficiency. It begins by defining market liquidity and various liquidity measures, including trade-based and order-based metrics, are discussed. The review then addresses market informational efficiency, outlining Fama's (1970) efficiency forms and their implications. Finally, the link between liquidity and efficiency is explored, with a focus on how liquidity affects price discovery and market efficiency, supported by both theoretical and empirical findings.

2.1. Market Liquidity: Definition

Market liquidity has been defined in various ways. A common definition of stock liquidity (liquidity of shares) is the ability to buy or sell shares immediately and in high volumes without adversely affecting the prices and without causing an increase in transaction costs (Utami et al., 2020).

This definition identifies three key liquidity factors: execution cost, quantity, and time. Brunnermeier (2009) described these as the bid-ask spread (the loss incurred when selling a stock and immediately repurchasing it), market depth (the volume of stocks traded without significantly impacting the price), and market resiliency (the speed at which a price recovers to its ‘normal’ level after a drop). According to Harris (1990), a perfectly liquid market is characterized by the ability to convert any amount of a given security into cash and back to securities instantaneously and without any cost. Indeed, a liquid market is one where transaction costs for such conversions are minimized.

2.2. The Measurement of Market Liquidity

Liquidity measures are generally classified into two categories: trade-based measures and order-based measures. Trade-based liquidity measures encompass trading volume, trading value, turnover ratio and the number of trades. These indicators are attractive due to their accessibility and broad acceptance among traders. Nevertheless, they are ex-post metrics, meaning they reflect past trading activities rather than providing real-time or forward-looking insights.

Order-based liquidity measures derive from the information contained in the order book and serve as ex-ante indicators, offering insights into both the feasibility and costs of executing immediate trades. Most of these measures focus on bid-ask spread, which illustrates an approximation of the expenses an investor faces when executing a trade right away (Galliani et al., 2014). In essence, When buying or selling a stock, investors must cross the bid-ask spread and transact at the prevailing bid-ask prices in order book. Measuring this cost as a percentage of the stock price (relative spread) allows for liquidity comparisons across stocks with varying price levels (Aitken and Comerton-Forde, 2003).

2.3. Market Informational Efficiency: Definition

According to Fama (1970), Market Informational Efficiency asserts that asset prices comprehensively incorporate and represent all accessible information. To be more precise, in a market characterized by informational efficiency, changes in asset prices result from news that cannot be systematically predicted (Abounoori et al., 2012). This implies that asset prices only react to the unexpected components of news, since the expected elements of the news is already reflected in the current prices and so earning higher profits without taking on additional risk is impossible (Shostak, 1997).

There are three classical forms of market efficiency: weak, semi-strong and strong form. In the case of the weak-form efficiency all past prices are incorporated into the current market price. This basically implies that it is not possible to get any significant advantage on the market solely through the analysis of past prices, as it is done in the case of technical analysis. For the stock market, this indicates that no profitable information regarding future stock price movements can be derived by examining historical stock prices (Serbinenko & Rachev, 2009).

The semi-strong efficiency incorporates all publicly available information into prices immediately, while strong-form includes all information, both public and private. In practice, the weak form is the most extensively studied, whereas the strong form is less analyzed due to the inherent difficulty in identifying private information (Hodera, 2015).

2.4. The Links between Market Liquidity and Market Efficiency

Recent findings show that liquidity fluctuates over time, and market conditions can become highly volatile, leading to significant increases in trading costs and decline or even complete absence of liquidity. A crucial question that has not yet been explored is whether changes in liquidity are linked to changes in efficiency.

Numerous theoretical frameworks and increasing empirical evidence indicate a link between market liquidity and informational efficiency. Admati & Pfleiderer (1988) highlight that markets can become more liquid due to reduction in tick size. This increased liquidity enables markets to incorporate private information more effectively as an external decrease in trading costs can encourage trading based on information related to fundamentals. Consequently, such changes may enhance the overall efficiency of the market by facilitating more informed trading.

Kyle (1985) argues that as liquidity increases, informed traders become more aggressive in executing trades based on their information, as their trades exert a smaller impact on prices. Moreover, liquid markets provide greater incentives for informed traders to acquire more precise information. Conversely, in illiquid markets where trading costs are high, informed traders may be less active, leading to significant deviations of security prices from their fundamental values. An alternative perspective posits that liquidity serves as a proxy for non-informational trading, commonly referred to as noise trading, which can negatively affect informational efficiency.

Behavioral finance models highlight how constraints on arbitrage limit the ability of rational investors to counteract the effects of noise traders. According to DeLong et al. (1990), rational arbitrageurs might even amplify demand shocks caused by noise traders if they expect short-term mispricing to intensify. If liquid markets experience higher levels of noise trading compared to illiquid markets, and rational agents do not fully counteract the influence of noise traders, then asset prices in liquid markets may be less efficient than those in illiquid markets (Tetlock, 2008).

Since market liquidity reflects market depth and the ability to absorb risk premiums in trade execution, it can be considered a key factor influencing the price discovery function. When market efficiency is viewed through the lens of price discovery and the informational content of prices, liquidity plays a role in shaping market price uncertainties—either by limiting the extent to which prices fully incorporate available information or by causing temporary deviations from market-clearing equilibrium prices. Consequently, an increase in market liquidity, accompanied by a reduction in liquidity premiums such as the bid-ask spread and market impact, can enhance efficiency by reducing price uncertainties. Understanding the mechanisms through which market liquidity influences price discovery can provide valuable insights for developing strategies aimed at improving market efficiency (Muranaga & Shimizu, 1999).

Chordia et al. (2008) present three competing theoretical perspectives regarding how return predictability arises from order flows. The first scenario suggests that when market makers possess restricted capacity to bear risk, persistent asymmetric order flows may cause temporary price deviations from their fundamental values, leading to predictable returns over short horizons.

Market participants including floor traders and brokers, who are able to identify these price deviations, may engage in arbitrage trades that facilitate the rapid convergence of prices toward their fundamental values. Nevertheless, market illiquidity can discourage these arbitrage activities by raising transaction costs and associated risks. Moreover, agents such as day traders, floor traders and brokers who actively monitor the market, may identify divergences between midquotes and true value of assets. Arbitrageurs may submit orders to take advantage of short-term discrepancies between midquotes and their fully-informed equivalents. When these arbitrage orders arrive in sufficient quantities and are executed in a timely manner, they can effectively diminish the excess inventories held by market makers.

This action leads to a swift adjustment of midquotes in response to initial imbalance shocks, thereby diminishing return predictability. However, arbitrageurs are typically more inclined to place such orders when the bid-ask spread (a common indicator of market illiquidity) is narrow. This reasoning implies that highly liquid markets tend to have lower return predictability, whereas less liquid markets may display more pronounced predictability.

While the previous argument indicates that liquidity diminishes return predictability from order flow, alternative hypotheses exist. For instance, if market makers underreact to order flow due to cognitive limitations, other market participants may find it profitable to gather and trade on order flow information. This would enhance efficiency by prompting prices to adjust more fully to order flow. However, the activity of these informed traders would also increase adverse selection risk faced by market makers, potentially leading to a decline in market liquidity. Under this scenario, lower liquidity could be associated with greater market efficiency.

A third hypothesis suggests that if external intervention is unnecessary and rational market makers efficiently manage imbalances by adjusting their quotes, illiquidity may have no systematic relationship with the predictability of returns based on order flow.

2.5. Empirical Studies

The link between market liquidity and informational efficiency has been a subject of considerable interest in financial studies. Scholars have sought to understand how liquidity affects the ability of markets to incorporate and reflect all available information in asset prices. The initial research in this issue traces back to the 1990s. Among the first scholars to examine this relationship was Kyle (1985), who, in his seminal paper "Continuous Auctions and Insider Trading," developed a framework to analyze the role of liquidity in the price discovery process. He demonstrated that increased liquidity enables informed traders to incorporate their private information into prices at a lower cost, thereby enhancing informational efficiency. Similarly, Admati and Pfleiderer (1988), in their paper "A Theory of Intraday Patterns: Volume and Price Variability," investigated how variations in transaction costs and liquidity influence market efficiency. They showed that when liquidity costs decrease, markets assimilate information more rapidly, thereby progressing toward greater efficiency.

The majority of studies have found a positive link between liquidity and efficiency, suggesting that increased liquidity contributes to greater efficiency:

Cajueiro & Tabak (2004) found that liquidity and market constraints are crucial in analyzing market efficiency, with the Hong Kong stock market being the most efficient among the three Asian markets studied including China, Hong Kong, and Singapore. Their results emphasized the role of liquidity in enhancing efficiency. Chordia et al. (2008) observed a positive link between liquidity and efficiency. Their research, focusing on 193 companies listed on the New York Stock Exchange, suggested that higher liquidity fosters greater arbitrage activity, ultimately enhancing efficiency. Bariviera (2011) also highlighted a significant positive effect of liquidity on informational efficiency. Using the Hurst exponent and DFA method in Thailand Stock Exchange, the study concluded that liquidity enhances market informational efficiency. Hodrea (2015) using panel data analysis showed that increased liquidity leads to improved informational efficiency in the Romanian financial market. Salehifar (2021) in the context of the cryptocurrency market, found that higher liquidity leads to more unpredictable return behavior, aligning with the Efficient Market Hypothesis. In these markets, high liquidity makes return predictability difficult, potentially reducing informational efficiency due to the dominance of noise trading and random fluctuations. Zhao (2023) concluded that increased liquidity leads to improved informational efficiency in China's stock market from 1998 to 2017, especially when liquidity is driven by regulatory changes such as reductions in stamp duty.

Some studies such as Sarkanian et al. (2015) have suggested that there may be a negative link between liquidity and efficiency. They explored the Iranian stock market from 2002 to 2013, finding that a significant inverse relationship existed between liquidity and stock returns as measured by Amihud's illiquidity proxy. This suggests that higher liquidity may reduce efficiency in certain market contexts.

A number of studies have reported that there is no significant connection between liquidity and efficiency. For example, Sukpitak & Hengpunya (2016) examining both developed markets and emerging markets from 2005 to 2015 found that trading volume, as a proxy for liquidity, had little to no impact on efficiency. The cross-correlation values were close to zero, indicating an insignificant effect of liquidity on efficiency.

The aforementioned studies have been summarized in the table below. Despite the wealth of literature exploring this relationship, there remains a significant gap in the understanding of the variable nature of the liquidity-efficiency link. Most studies tend to focus on one-dimensional conclusions—either a positive, negative, or neutral relationship—without considering that this relationship could fluctuate over time or in different contexts. In this regard, while existing research has provided valuable insights, the current study aims to offer a more nuanced perspective by analyzing how market liquidity and informational efficiency interact, not just in a static form but in a dynamic manner that can shift based on various factors. This approach is particularly significant when applied to developing markets, such as Iran, where market conditions are often more volatile and unpredictable than in developed economies.

Table 1. Summary of Empirical Studies on Liquidity and Efficiency

Researchers	Market & period under consideration	Methodology	Result
Cajueiro & Tabak (2004)	China, Hong Kong, Singapore (1992–2000)	long-term memory dependence method	Positive
Chordia et al. (2008)	NYSE (USA) (1993–2002)	Order flow analysis	Positive
Bariviera (2011)	Thailand (1975–2010)	DFA method	Positive
Hodrea (2015)	Romania (2011)	Panel data analysis	Positive
Sarkanian et al. (2015)	Iran (2002–2013)	Portfolio formation method	Negative
Sukpitak & Hengpunya (2016)	USA, Japan, Hong Kong, India, Korea, Thailand (2005–2015)	DCCA method	Neutral
Salehifar (2021)	Cryptocurrency market (2015–2018)	Autocorrelation & long-term memory tests	Positive
Zhao (2023)	China (1998–2017)	Panel regression	Positive

Source: *Summarized by the author based on various empirical studies*

3. The Study Model

Detrended Cross-Correlation Analysis (DCCA) was introduced by Podobnik & Stanley (2008) to determine long-term correlations between two large non-stationary time series with power-law distributions and temporary fluctuations. This method has been widely used for studying various time series (Podobnik et al., 2009; Zebende & Machado Filho, 2009; Wang et al., 2010; Liu & Ma, 2014; Zhao et al., 2018; Zou & Zhang, 2020; Rodriguez & Alvarez-Ramirez, 2021; Hou & Pan, 2022; Shahrazi & Shahrazi, 2023; Wu et al., 2024).

A review of these studies reveals that DCCA has applications in various fields, including financial data analysis, stock market prediction, and examining link between economic variables. It can also be employed in other areas, such as environmental data analysis, social science research, and medical studies. Additionally, DCCA serves as a tool for uncovering hidden patterns and gaining a deeper understanding of complex fluctuations in data.

DCCA is based on Detrended Fluctuation Analysis (DFA), proposed by Peng et al. (1994). DCCA allows for analyzing long-term correlations between two time series. This method helps detect the impact of temporary changes and fluctuations over the long run, revealing whether variations in one variable can persistently influence the other.

Findings may indicate that, despite significant short-term fluctuations, there exists a meaningful positive or negative long-term correlation between these variables or vice versa. In financial markets, such insights can assist investors and analysts in designing more effective investment strategies.

The steps of DCCA method are reviewed in following section.

If we consider two time series, x(i) and y(i), where i=1, 2, …, N and N represents length of both series, the first step involves constructing Equations (1) and (2). In these equations, x and y show values of the series x(i) and y(i), respectively. The mean of each series is defined as the average value of the data points within that series.

$$X(i) = \sum_{t=1}^{i} [x(t) - \langle x \rangle] \quad (1)$$

$$Y(i) = \sum_{t=1}^{i} [y(t) - \langle y \rangle] \quad (2)$$

In the second step, the series X(i) and Y(i) are divided into M=int(N/n) non-overlapping boxes of equal length n. These boxes are indexed as m=1,…, M and i_{nm} denotes their starting time.

In the third step, for each m-th box of size n, least-squares trend lines $X_{nm}(i)$ and $Y_{nm}(i)$ are fitted as local trend lines corresponding to the data in that box.

In the fourth step, detrending is performed by subtracting the local trends $X_{nm}(i)$ and $Y_{nm}(i)$ from original series X(i) and Y(i), respectively. The covariance of the detrended series is then computed according to Equation (3).

$$F_{DCCA}^2(n) = \frac{1}{M} \sum_{m=1}^{M} \left\{ \frac{1}{n} \sum_{i=i_{nm}}^{i_{nm}+n-1} [X(i) - X_{nm}(i)] \cdot [Y(i) - Y_{nm}(i)] \right\} \quad (3)$$

It is assumed 5<n<N/5.

When x(i)=y(i), the $F^2_{DCCA}(n)$ function reduces to detrended variance $F^2_{DFA}(n)$.The linear relationship between $F_{DFA}(n)$ and n in log-log plot provides evidence of a power-law distribution.

Moreover, slope of linear relationship between $\log F_{DFA}(n)$ and logn can be used as the Hurst exponent (H), which helps determine whether the series exhibits persistence (H > 0.5) or anti-persistence (H < 0.5). For H=0.5, the series is uncorrelated (white noise), and its behavior aligns with the Efficient Market Hypothesis (EMH), making it unpredictable. In other words, the closer H is to 0.5, the more efficient the market is.

The ρ_{DCCA} coefficient, introduced by Zebende (2011) to measure how two non-stationary time series are related, is calculated by dividing the detrended cross-covariance function F^2_{DCCA} by the product of the detrended variance functions $F_{DFA,x}$ and $F_{DFA,y}$ from x(i) and y(i). That is:

$$\rho_{DCCA}(n) = \frac{F_{DCCA}^2(n)}{F_{DFA.x}(n) F_{DFA.y}(n)} \quad (4)$$

Notably, Equation (4) helps quantify the cross-correlation between non-stationary time series. The value of $\rho_{DCCA(n)}$ varies between -1 and 1, where 1 indicates perfect cross-correlation, -1 represents perfect inverse cross-correlation, and 0 suggests the absence of cross-correlation (Zebende, 2011; Podobnik et al., 2011).

Since efficiency evolves over time, to determine its value at a specific moment, the Hurst exponent (H) should be calculated over a relatively short time window (local cumulative component). Moreover, continuously computing H over time enables tracking the evolution of efficiency. This approach was referred to as the time-varying cumulative component in the study by Muniandy et al. (2001) and has been widely cited in stock market research (Grech & Mazur, 2004; Alvarez-Ramirez et al., 2008; Rizvi et al., 2014).

In this study, H values are estimated using the DFA method, and the evolution of H over time is presented using one-year rolling windows.

H is calculated for the first 241 returns[1], after which first return is discarded, and next return from the time series is included in the calculation. This process is repeated iteratively until end of the dataset. As a result, the sample size remains constant in each evaluation.

In the context of financial markets, when the H value for asset prices or returns is closer to 0.5, the market exhibits characteristics more aligned with an ideally efficient market. Accordingly, an efficiency index is explicitly introduced in Equation (5) (Wang et al., 2010; Gu et al., 2013; Wang & Hou, 2015).

$$\mathrm{EI} = |\mathrm{H} - 0.5| \quad (5)$$

Based on this equation, the lower the Efficiency Index (EI), the higher the market efficiency.

In the present study, to represent market activity on a daily basis, both trading volume and the Overall Stock Index are considered. Since these data are readily accessible, trading volume will be used as the basis for evaluating market liquidity in this study. Additionally, since the EI index is time-varying with a one-year rolling window and represents efficiency, the one-year moving average of trading volume (V) will be used as a representative of liquidity.

In this regard, V is measured by first calculating the average trading volume for the first 241 days, then discarding the first volume and including the next one in the series. Similarly, the subsequent steps are continuously repeated until end of the data. As a result, each trading volume average is computed using data samples of same size.

As mentioned in previous section, the samples consist of closing prices (for calculating efficiency using the DFA method) and trading volumes from the TSE. The selected period spans from March 2010 to March 2024. All time series data were collected from the Tehran Stock Exchange website (www.tse.ir).

4. Empirical Results

The measured values of the EI and the V for the Tehran Stock Exchange are shown in Figures 1 and 2. As seen in the charts, efficiency experiences sudden changes during certain periods, while V (a liquidity measure) changes more gradually.

[1] The average number of trading days per year during the period from March 27, 2010 to March 18, 2024.

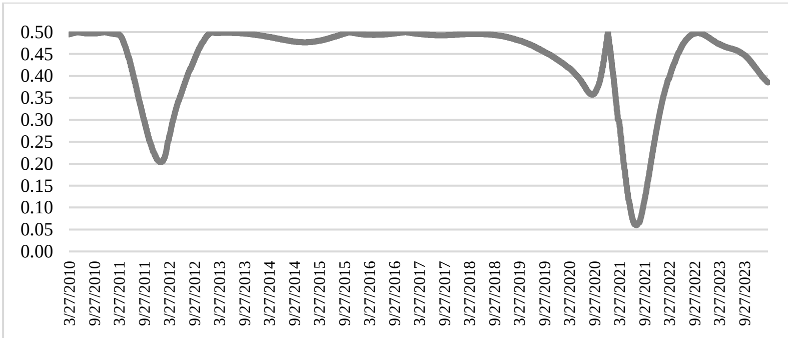

Figure 1. Time-varying EI with one year rolling window

***Source:** Research finding*

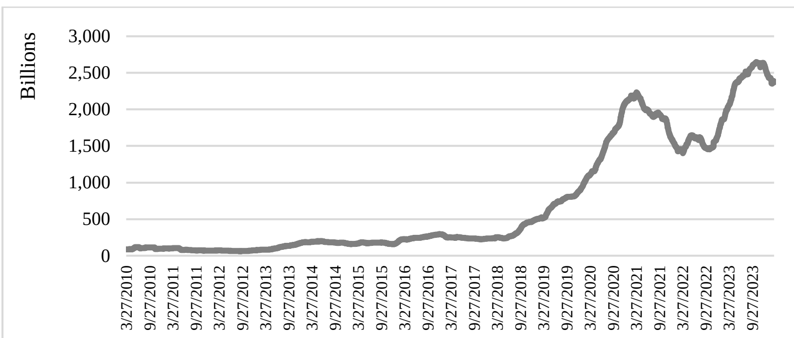

Figure 2. The V for Tehran Stock Exchange

***Source:** Research finding*

The descriptive statistics for the Efficiency Index and trading volume are summarized in Table 2. Accordingly, the mean of the Index is 0.439, indicating that efficiency in Tehran Stock Exchange has generally been low during the studied period. This implies that asset prices do not fully and promptly reflect available information, creating opportunities for informed traders to earn abnormal profits. In this context, the maximum value of the Efficiency Index (representing the lowest efficiency) is 0.499 (corresponding to 08/12/2010), and the minimum value (representing the highest efficiency) is 0.060 (corresponding to 01/08/2021). This range indicates that efficiency has undergone significant changes over time. Factors such as information asymmetry, trading restrictions, market manipulation, as well as behavioral, economic, and political influences can play a substantial role in the efficiency during different periods.

Additionally, the skewness of this variable is -2.19, indicating that the distribution of the Efficiency Index is left-skewed. In other words, the majority of the data points are larger than the mean, suggesting that there are more values on the right side of the distribution, with lower efficiency observed in most of the sample observations. The kurtosis value is 7.42, which is above normal, indicating that the distribution of efficiency values is highly peaked and that, in many periods, these values are close to the mean. In other words, there has been relative stability in efficiency during most periods.

On the other hand, the average trading volume (as a measure of market liquidity) during the studied period was approximately 2.55 billion shares, with a maximum of 64.1 billion shares (recorded on 28/11/2022) and a minimum of 45 million shares (recorded on 27/03/2010). Factors such as the release of significant news, changes in policies and macroeconomic variables, alterations in market-related regulations and policies, and international events are among the most important drivers of changes in market trading volume. Furthermore, the skewness of this variable is 35.43, indicating a rightward skew. In other words, the majority of trading volume data points are smaller than the average, which could be indicative of a period of market stagnation or low activity. In addition, the kurtosis of this variable is 3.84, exceeding that of a normal distribution, suggesting that the distribution of efficiency values is slightly peaked and these values are close to the mean in most periods.

Table 2. Descriptive statistics of efficiency and trading volume in Tehran Stock Exchange

Variable	Mean	Median	Max	Min	Std. Deviation	Skewness	Kurtosis
EI	0.439	0.483	0.499	0.06	0.09	-2.19	7.42
V*	2.55	0.849	64.1	0.008	3.85	3.84	35.43

* *The unit of trading volume is billions of shares.*
Source: *Research finding*

To determine the type and extent of correlation between efficiency and liquidity, DCCA method was applied to the series of EI and V, and the results are shown in Figure 3. It is clearly observed from this chart that the correlation between the Efficiency Index and trading volume is not constant and changes over time, with both positive and negative correlations being visible, although their magnitudes are not very high. In other words, it is difficult to make a precise and definitive statement about the type and extent of the correlation between the efficiency index and trading volume in Iranian stock market.

It can be inferred that the observed temporal changes in correlation coefficient between these two variables suggest that this relationship depends on the length of the rolling window and the number of observations. In this context, the DCCA values in Tehran Stock Exchange were close to zero for many periods, with the exception of the period from 21/07/2010 to 02/11/2011, where the correlation during other periods was between -5% and 5%, indicating a very low correlation. This means that changes in EI rarely correlate with changes in V. In other words, market liquidity has little impact on efficiency and vice versa. This may be because other factors, such as information flow, changes in regulations and market structure, the entry of new investors, behavioral factors, and economic and political developments, play a more significant role in determining both trading volume and market efficiency.

This conclusion is consistent with studies by Bariviera (2011) and Sukpitak & Hengpunya (2016), which investigated the correlation between efficiency and liquidity in selected countries including the United States, Japan, Hong Kong, India, South Korea and Thailand. In contrast, the results are contradicted by several studies (Cajueiro and Tabak, 2004; Oh et al., 2007; Chordia et al., 2008; Bariviera, 2011; Senssoy, 2013; Hodrea, 2015; Salehifar, 2021 and Zhao, 2023). However, these conflicting results may be due to the use of different liquidity measures, differing market conditions, and variations in the periods examined. Furthermore, trading volume often increases over time, with its values becoming unbounded, whereas the Efficiency Index is certainly limited (the closer the EI value is to 0, the higher the efficiency). Therefore, it seems that in the long run, trading volume will be increasingly less correlated with efficiency.

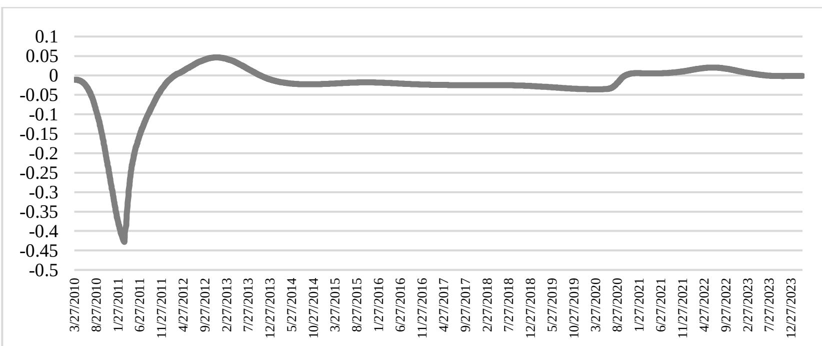

Figure 3. DCC coefficient between the EI and the V on the Tehran Stock Exchange
***Source:** Research finding*

The descriptive statistics for the cross-correlation coefficient between the EI and the V are summarized in Table 3. Accordingly, the mean cross-correlation coefficient is -0.026, indicating that the correlation between the EI and the V (a liquidity indicator) in Tehran Stock Exchange during the period under study has been very low on average, close to zero.

Additionally, the maximum cross-correlation coefficient is 0.046, while the minimum value is -0.428. The skewness is -3.58, indicating that the distribution of the cross-correlation coefficient is left-skewed. In other words, the majority of the correlation values are larger than the mean (-0.026), suggesting that there are more values on the right side of the distribution, with low correlation coefficients. The kurtosis value is 17.51, which indicates that the distribution of correlation coefficients is very peaked, with many values clustered around the mean.

Table 3. Descriptive statistics of the DCC coefficient

Variable	Mean	Median	Max	Min	Std. Deviation	Skewness	Kurtosis
DCC coefficient	-0.026	-0.019	0.046	-0.428	0.068	-3.58	17.51

***Source:** Research finding*

5. Concluding Remarks

This study examined the cross-correlation between market efficiency and trading volume (representing liquidity) in TSE from March 2010 to March 2024. In this regard, the market efficiency index time series was first calculated based on a rolling one-year window and daily closing prices. Then, the trading volume series for the same period was created using the one-year moving average of daily trading volumes. Finally, to analyze the level of cross-correlation between the two series, the DCC coefficient was applied.

The results of the analysis revealed that the correlation between efficiency and liquidity is not constant and changes over time, with both positive and negative correlations being observed, although their magnitudes were relatively low. In other words, a precise and definitive statement regarding the type and degree of correlation between efficiency and liquidity in Iranian stock market cannot be made. In this context, the correlation coefficients were very low and close to zero for most periods. In other words, market efficiency has little or no correlation with its liquidity. Therefore, the findings suggest that market liquidity has not had a significant impact on efficiency in Tehran Stock Exchange and vice versa. Therefore, an increase or decrease in trading volume does not necessarily lead to an improvement or decline in efficiency, and vice versa. This indicates that the relationship between these two variables is complex and can be influenced by various factors including market structure, regulations, information flow, and entry of new investors, behavioral characteristics, and economic and political developments. The results of this study are consistent with some previous studies (Sukpitak & Hengpoonya, 2016) but contradict others (Cajueiro & Tabak, 2004; Oh et al., 2007; Chordia et al., 2008; Bariviera, 2011; Sensoy, 2013; Hodrea, 2015; Salehifar, 2021 and Zhao, 2023), likely due to the use of different liquidity measures, differing market conditions, and variations in the periods examined.

According to the results of this study, it can be inferred that the link between efficiency and liquidity in Tehran Stock Exchange (TSE) is weak and variable. Accordingly, increasing trading volume and market liquidity does not necessarily translate into greater efficiency, and other influential factors must be considered to enhance efficiency. In this framework, improving the structure of the capital market and its governing regulations, in order to increase transparency, reduce transaction costs, and facilitate access to information, can help to increase trading volume and improve market efficiency. Strengthening the role of active financial institutions in the capital market, such as investment funds and portfolio management companies, beside increased investor education, can also reduce speculative and irrational behaviors and lead to higher market efficiency.

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The authors declare no conflict of interest.

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