Adv. Math. Fin. App., 2023, **8**(2), P. 985-1006

Advances in Mathematical Finance & Applications
www.amfa.iau-arak.ac.ir
Print ISSN: 2538-5569
Online ISSN: 2645-4610
Doi: 10.22034/amfa.2022.1957711.1744

Applied-Research Paper

Stock Liquidity and Return Predictability; Is There a Connection? (Evidence from an Emerging Market)

Mojtaba Alifamian[a]*, Ali Eshaghzade[b*], Abdolkarim Maleknia[a]

[a] *Department of Accounting, Allameh Tabatabai University, Tehran, Iran*
[b] *Department of Finance, Petroleum University of Technology, Tehran, Iran,*

ARTICLE INFO
Article history:
Received 2022-04-28
Accepted 2022-09-05

Keywords:
Liquidity, Spread, Return Predictability, Market Efficiency, Tehran Stock Exchange.

ABSTRACT

This study examines the relationship between stock liquidity and return predictability of 116 publicly-traded firms in Tehran Stock Exchange (TSE). To this end, we constructed a dated-regular frequency of time series with total 40128 stock-firm observations. After calculating daily bid-ask spreads and stock returns, the observations were classified based on liquidity into three classes and the return predictability was investigated across different classes using a set of parametric tests. The results exhibit signs of return autocorrelation and non-independence over three liquidity groups. Our findings didn't show a connection between stock liquidity and market efficiency. The Hurst exponent also revealed mean reversion of returns series across different liquidity classes. We conclude that stock liquidity doesn't play a significant role in market efficiency and return predictability of stocks in TSE. In case of TSE as other emerging markets, due to the small number of traders (the need for more trading activity) and low market making activities, both the cost of trading increases and the reaction to stock price information is delayed, resulting in predictability of price /return.

1 Introduction

Information is one of the most important factors in financial markets and the existence of information symmetry in transactions indicates the efficiency of markets. Information efficiency and proper pricing system leads to market development in the long run [48]. Information asymmetry will create various risks, especially for traders. Information risk is extremely important in stocks that have less liquidity and fewer transactions, and neglecting price information and risks associated with trading can be detrimental to investors. In a full-fledged efficient market, securities prices are heavily influenced by the information available in the market [8], and investors cannot gain abnormal profits. In such market, the price of securities is close to intrinsic value. If some information is not reflected in the stock price, then the market is not efficient and the prices don't follow a random walk process [41]. In the weak form of efficiency, some information is relevant to prior periods and their impact on securities prices is reflected. However, in and efficient market, prices are highly influenced by information, both public and non-

* Corresponding author Tel.: +98*9379530076*
E-mail address: *mojtaba.alifamian@yahoo.com*

public without any momentums or mean reversion [59]. Price efficiency refers to the extent to which the security market price is informed and contextually reflects actual underlying economic facts [8]. Prices are formed through market mechanism and information collected by market participants regarding stock characteristics [31]. Hence, stock prices represent investors 'expectations [28]. Stock liquidity increased the number of informed investors and improve the quantity and quality of information that can be included in prices. Increase in stock liquidity causes current price closer to intrinsic value. In other words, it makes the stock price more efficient [52]. Liquidity is one of the main characteristics of an efficient market; a permanent concern of supervisory and enforcement authorities [27]. Markets with the appropriate liquidity level allow entry and exit to the market with the least disruption and transaction costs [10]. It also has a profound effect on the stability of financial systems, since high liquidity markets can better absorb systematic shocks. A high-liquidity market allows investors to trade at a rational price, minimum cost, and at a higher speed [61]. Increasing liquidity raises the informativeness of stock prices. This allows prices to follow a random walk and stochastic path [16, 59]. Return predictability diminishes through arbitrage trading, which will be more extensive and effective during times in which the market liquidity is high [13]. The empirical findings across developed markets provide direct connections between liquidity and price unpredictability for different classes of assets from stocks [58, 13] to cryptocurrencies. Chordia, et al. [13] argued that exogenous declines in quoted bid-ask spreads result in stock liquidity improvements. Such increases in liquidity stimulates market efficiency.

Liquidity vary over time and market situations and facts can occasionally be so stochastic that trading costs jump dramatically to diminish stock liquidity. An important but unaddressed empirical question in TES is whether such variations in stock liquidity are connected to price/return predictability and fluctuations in market efficiency. Amihud & Mendelson, [3] as well as Jacoby et al., [37] provide a connection between liquidity and stock returns in ways of premium demanded by investors for trading illiquid stocks. They provide theoretical arguments and empirical evidence to support the liquidity risk-premium. Jones and Amihud concluded that liquidity explains expected returns. Pastor & Stambaugh [46] and Acharya & Pedersen [1] show a cross sectional relation between expected stock returns and liquidity risk. But we explore a distinctly different intercommunication between stock liquidity and return through studying liquidity associations with intraday market efficiency. Efficient market Fama, [19] accentuates a lack of return predictability as the criterion for efficiency and return predictability is one of the anomalies that violates the efficient market hypothesis. The study unveils the effects of liquidity on return predictability to show how liquidity may govern information efficiency. However, we address the question by using daily return and effective spreads data for a large sample TSE trading stocks of 116 firms over two-year period (2018–2019). The results can be significant; because investors consider liquidity just as risk and return. The impact of this feature of securities on capital market efficiency, is the subject of much financial research. Nowadays, the efforts of market authorities in terms of service development, trading regulatory and market structure reforms are perceivable and aimed to increase efficiency and liquidity of capital markets [2].

We investigate return predictability through order flows in a comprehensive sample of TSE actively traded stocks over more than 350 trading days and 40128 observations. From a theoretical point of view, as far as the researcher is aware, no research has examined and analyzed stock liquidity and its impact on capital market information efficiency in the Tehran Stock Exchange. Failure to examine this issue is one of the theoretical gaps in previous research that this study seeks to bridge by examining the effect of stock liquidity on the predictability / non-predictability of returns as a reflection of capital market information efficiency. From a methodological point of view, in a few studies, variables such as zero return and Amihud have been used to measure stock liquidity, while this study tries to compensate for these shortcomings by considering the variable based on the price gap of sales quotes as a measure of liquidity. Also several parametric and non-parametric tests (time series persistence test, autocorrelation test, observation independence test and long-term memory) are used simultaneously to obtain reliable results. Practically, this research is conducted in Tehran Stock Exchange, which has much lower levels of efficiency and transparency than the world's advanced stock exchanges, and predicts the impact of policies, strategies and measures of liquidity on information efficiency and asymmetry. This paper is organized as follows: second and third sections are dedicated to hypothesis development and design, respectively. Section four presents data analysis results. Eventually, the final section is devoted to conclusions.

2 Literature Review

Liquidity refers to how fast an asset or stock can be sold at an intrinsic value on the market. The more transactions for a stock means the more buyers and sellers are trading and this implies more liquidity [15]. In other words, if an asset can be converted into cash with high speed and hassle-free, its liquidity is higher. Liquidity enables the holders of some assets, such as stocks, to buy, maintain, and sell at the right time without worrying about the buyer for their assets [52]. If there is a large volume of stock trading in the market so that stock trading in the market is not dominated by the seller or the buyer, the price offered by the seller per share (bid price) or the price that the seller is willing to accept (asking price) will be almost close to each other. So investors will not have to spend a fortune to sell fast. When the difference between bid and ask prices increases, market liquidity disappears [19]. The role of the liquidity factor in the valuation of assets is due to the crystallization of the concept of risk of lack of liquidity of the asset in the mind of the buyer, which can cause the investor to withdraw from the investment [14].

The higher the risk of an asset, the more the investor expects to gain a return, and one of the most important factors affecting the risk of an asset is its liquidity. The lower liquidity of a stock, the less attractive that stock will be to investors, unless the owner expect a higher return [22]. According to risk-premium theory, less liquidity equals more risk, and more risk is associated with higher expected returns. But at the macro level, it is expected that as the stock becomes more liquid, it will contain new information about the gradual changes in stocks that will lead to higher returns [48]. So far, different criteria have been proposed to measure the stock liquidity factor, which in a general classification can be divided into four main groups as follows:

- Transactions cost –based: This criterion is based on the transaction costs of financial assets in the market. The price gap between bid and ask may cover almost all of these costs, these price gaps are usually considered as a measure of liquidity [12].
- Trading volume-based: As the name implies, these criteria identify liquidated markets through trading volume in comparison with price changes, which are used to measure the size, extent and depth of liquidity. Among the liquidity criteria in this category, we can mention Amihud and turnover ratio [12, 19].
- Market-based criteria: In this criterion, an attempt has been made to measure the elasticity of price discovery by distinguishing between price changes due to the degree of liquidity and other factors such as general conditions or the entry of new information [19, 22].
- Equilibrium price-based criteria: This criterion seeks to measure regular movements towards equilibrium price in order to mainly measure the elasticity dimension [14].

Theoretical literature in the field of market research has a very long history. In modern finance, there has been a lot of research to determine the relevant components of the stock market. At the same time, part of the investor community has always been trying to follow rules of the deal. These rules are designed to enable profitability based on predictable components [14]. Most of financial theories has been developed based on random walk models for price and return. In an efficient market, all the surrounding information is reflected in the current stock price, so it is not possible to predict future prices (returns) and returns take a triangulate mode [59]. Informational efficiency means that information on the value of assets equally and, of course, at the right speed, are available to all market participants, and certain investors cannot generate abnormal return proportional to risk taken, through information asymmetry [61]. In the weak form of market efficiency, the set of information that is available and affects stock prices is only relevant to past period information. In this case, it is assumed that the price of securities only reflects historical information [54]. In the semi-robust form of performance, the available data set includes all general information; While in the strong form of performance, which includes the two previous forms, stock prices reflect all information, both public and confidential [27]. In an efficient market, the basic premise is that the price of securities reflects the impact of all information about current events or events that the market expects to occur in the future [22]. A prerequisite for market efficiency is the rapid and complete reflection of new information on the price of securities [14]. If the capital market is efficient, both the price of securities will be determined correctly and fairly, and the allocation of capital, which is the most important factor of production and economic development, will be done optimally and optimally [22]. The efficient market hypothesis, based on the rational investors' use of all available information, claims that prices can accurately reflect all available information, and that price changes in such a market over time are random and unpredictable, but there are some exceptions that show in the meantime some stocks are more profitable than others [18]. According to the market efficiency hypothesis, the performance of each stock portfolio is independent of its performance in the past, and in situations where the market loses its efficiency relatively, it is possible to increase the return on investment through appropriate investment strategies. One of these strategies is to use a portfolio strategy consisting of value stocks based on financial accounting information [12]. This strategy was first used by Piotrosky [47]. on the US Stock Exchange.

According to the efficient market hypothesis, competition between investors to find exceptional profitability opportunities brings the market price closer to the intrinsic value of the asset [40]. Of course, the efficient market hypothesis does not assume that a number of investors behave quite rationally, but believes that the market behaves rationally, but the behavioral finance field believes that there are limitations in creating interaction as a result of arbitrage conditions [34]. As long as the sale is not short, it is considered a restriction on arbitrage [28]. Arbitrators still run the risk of not arbitrating when the market price is too far from the intrinsic price or large in pricing error [18]. Even the size of the market (market depth) is an important factor in the realization of arbitrage. In large markets (with great depth), arbitrage is possible. In these markets, there are many funds for arbitrage with many investors; But in smaller (shallow) financial markets, the possibility of arbitrage is minimized due to the lack of sufficient liquidity [27] & [48]. The efficient market hypothesis supports the concept of random walk; Because according to this theory, stock returns do not consist of past events or future events, but of current and existing facts and information about those stocks [19]. The rationale behind this concept is that the information available in the marketplace is random and unpredictable (with both directional and non-directional expectations). As a result, stock price changes in efficient markets must follow a random step process [22]. The efficient market has no memory. This interpretation means that it is not possible to conclude from yesterday's prices about tomorrow's prices [14].

Random walk is one of the methods of examining efficiency in financial markets. This theory states that stock price changes have the same distribution and are independent of each other, so past movements or the price trend of a stock or market cannot be used to predict its future movement. In short, the random walk theory, also called the random turn theory, implies that stocks have a random and unpredictable path. Someone who follows the random walk theory believes that it is impossible to do better than the market without taking additional risk [19]. In fact, price behavior is a function of a process called random walk [12]. These studies were led by Fama in 1960 to the efficient market hypothesis. According to the efficient market hypothesis, competition among investors for profit at any investment opportunity ultimately leads to a situation where the current price of tradable securities is an unbiased forecast of their intrinsic value [57]. According to this hypothesis, stock prices would be a reflection of all available information, and most of the research that followed was based on this hypothesis. The effectiveness of the efficient market assumption was such that many capital asset pricing models (CAPMs), arbitrage pricing theories, option pricing models, and many others were based on this assumption [22]. Long-term memory processes are an important part of time series analysis. Existence of long-term memory in return has important applications in examining market performance, pricing derivatives and portfolio selection. Long-term memory (also called long-term domain dependence) explains the correlation structure of time series values over long intervals [32]. The presence of long-term memory in a time series means that there is a correlation between its data even with a large time interval [22]. Because long-term memory is a special form of nonlinear dynamics, its modeling using linear methods is not possible and encourages us to develop and use nonlinear pricing models [16]. Despite long-term memory, derivatives pricing using traditional methods will not be appropriate. The existence of this feature is a reason for rejecting the market efficiency hypothesis. According to the efficient market hypothesis, asset prices should not be predictable using past data. The presence of long-term memory in the return on assets indicates the existence of autocorrelation between observations over a long period of time [52]. Therefore, past returns can be used to predict future returns, which makes it possible to use a profitable speculative strategy [19].

2.1 Hypothesis Development

An efficient market is one in which information and facts about corporate stocks quickly affect stock prices, and prices adjust themselves accordingly [40]. In fact, an efficient market provides investors with the assurance that they are benefiting from the same information, so an efficient market is a market that reflects the information and facts that are available in the market and is a guide for investors [50]. The concept of efficient market is based on the assumption that investors consider all relevant information in the stock price in their buying and selling decisions, and the stock price is a good indicator for determining the value of a security [42]. One of the anomalies that violates the efficient market hypothesis is the predictability of price. Fama [21] consider the efficient market as a market that is rapidly adapting to new information. Although adapting to new information is an important feature in the job market, it is not the only feature [12]. In an information-efficient market, price changes and subsequent stock returns are unpredictable if the news, benefits, and information of all market participants are well reflected by prices. Fama [20] argues that an efficient market is one in which prices always fully reflect all available information. According to the random walk theory, stock prices only decrease or increase in response to new information. Any information that can be used to predict the performance of a stock should be reflected in the stock price [27]. New information is unpredictable by the definition of an efficient market. Therefore, the movement of stock prices based on new information should not be predictable; That is, the initial tests of market performance are generally based on the random walk test of stock prices [40]. The rejection of the random walk model is considered a reason for market inefficiency; Therefore, the existence of any model for predicting stock returns indicates a violation of the efficient market hypothesis [14]. Stock liquidity as one of the most important fabrics of financial market, affects market efficiency and return/price predictability [13] & [59]. If an increase in the stock liquidity leads to an aggravation of noise trading, the risk of a market mistake in stock pricing is accelerated and results in subsequent price fluctuations [45]. A high degree of liquidity allows well-informed shareholders to take advantage of their personal information, thereby encouraging investors to learn more about stocks and deal on the basis of information [10]. This leads to information–based pricing of stocks [5]. Liquidity may affect price (return) predictability through some different ways. Improvement in liquidity increases the ultimate value of information and thus stimulates stock market participants to obtain current facts about the intrinsic value of companies. High liquidity also makes it easier for an informed investor to benefit from collected information. Holmstrom & Tirole [34]. Grossman & Stiglitz [29] argued that stock price predictability decreases with the increase of informed investors and the quality of information. In fact, increasing liquidity of stocks facilitates transactions between investors and thus speeds up the process of disclosing confidential information. This leads prices to be unpredictable (determined by future economic facts), not autocorrelated.

Liquidity facilitates block holder formations. Most of institutional block's trade based on current market fact and signals. This also results in market efficiency and allows prices to pursue a turbulent and unpredictable path [25]. High liquidity provokes arbitrage trading. Risk-based arbitrage causes long-term holding of an undervalued stock and/or short-term holding of a stock that is overvalued. Arbitrage traders are generally well aware of the information [7]. Hirshleifer et al., [32] found that arbitrage trading aligns the market price with intrinsic value of stocks and thus contributes to price and market efficiency and diminishes return predictability. Informational efficiency role of liquidity, helps stock prices to reflect the surrounding facts Luo, [44] not underlying historical events. Subrahmanyam and Subrahmanyam [54] argued that high stock liquidity increases the informational efficiency of stock prices through motivating arm's length and information-based transactions and pacify price predictability. Active traders are more likely to arbitrage any signs of return predictability. Illiquid stocks bear high transaction costs for investors, dealers and speculators to bid and ask due to higher spreads and higher transaction costs [59]. Furthermore, for very illiquid stocks, the lack of active traders also implies it would take longer for market participants to act on new information, leading to market inefficiency [50]. So, we can hypothesize that when stock liquidity increases, the return predictability diminishes to approach a random walk and martingale process. This adds to market efficiency. Return predictability diminishes via "arbitrage trading", which it is expected to be more effective for stocks that are more liquid [13]. Higher transaction costs in markets with low turnover disturb the ability for traders to act quickly and readily, leading to market inefficiency [59].

2.2 Literature Review

Some scholars have investigated liquidity effects on market efficiency. For example, Hou & Moskowitz, [35] investigated the effects of stock liquidity on stock issuance costs. They used turnover ratio and volume of transactions as liquidity measures and concluded that stock liquidity is an important indicator for the issuance costs of the stocks, and companies can reduce their stock issuance costs through increasing stock marketability. Vassalou & Xing [58] showed that a low liquidity could result in a higher stock return. This supports liquidity risk premium theory. Chordia et al., [13] unveil that liquidity ferments arbitrage activity, which, in turn, enhances market efficiency and reduces pattern predictability. Further, as the quoted bid-ask spread decreased (high liquidity), open-close as well as close-open return variance ratios increased, while return autocorrelations diminished. Ghojavand et al., [26] Investigate the effect of different levels of liquidity metrics on stock returns using the Fama and French four-factor model. The research method was done through the portfolio of sample member companies based on stock liquidity criteria. The results of this study show that different levels of liquidity metrics will have different effects on stock returns. Erza and Seifi [17] studied the effect of financial risks on the market efficiency on the Tehran Stock Exchange. The GMM generalized regression model is used to explain the efficiency.

The results show that financial risks have a significant effect on market efficiency.Fang [22] examines the effect of liquidity on stock price efficiency in the US Stock Exchange. The results indicate positive effect of stock liquidity on stock price efficiency. Bahar Moghaddam et al., [4] investigate the impact of stock liquidity on price informativeness and earnings management through accruals among TSE listed firms. The results revealed economic significant impact of stock liquidity on stock price informativeness and earnings management through accruals. Brogaard, et al., [10] argue that stock liquidity plays an informational role in pricing of securities and contributes to information efficiency of markets. Yahyazadefar et al., [62] examined the relationship between liquidity and stock returns on the Tehran Stock Exchange. They showed that there is a positive and significant relationship between the volume and stock returns. This may be due to the increasing attractiveness of liquid stocks and the increasing demand for such stocks. Rahmani et al., [49] argue that there is a positive and significant relationship between the level of institutional ownership and stock liquidity and the concentration of institutional ownership reduces the liquidity of companies' stocks. These relationships have been observed both in terms of trading criteria such as trading volume, percentage of floating stocks and the Amihud benchmark, as well as in terms of information criteria such as the price gap between stock supply and demand. Soheili and Amirian [53] show that there is a direct and significant relationship between stock liquidity and the amount of free float of companies. Also, a negative and significant relationship was observed between stock return rate and free float. Taherinia and Rashid Baghi [56] examined prediction the return fluctuations with artificial neural networks approach. found that there is meaningful relation between the market variables and return. Farshadfar and Prokopczuk [23] investigate Stock Return Forecasting Improving by Deep Learning Algorithm.

Their results indicate that the applied DP model has higher accuracy compared to historical average model. Samadi et al., [51] argue that the real and dynamic relationship between returns and stock market fluctuations in different time horizons. They showed that the wavelet variance of the rate of return varies in different industries. The return of investment companies on various time scales is equal to the investment return of the banking industry. Wang [59] examines market efficiency and liquidity status of wide cross-section of cryptocurrencies. He finds liquid markets benefit from strong efficiency and lower predictability. He argues that active traders are more likely to arbitrage away signs of return predictability. According to Wang et al., There is a positive and significant relationship between stock liquidity variables and skewness coefficients and returns. Increasing liquidity increases the coefficient of skewness and elongation and as a result distances the return from the normal distribution (unpredictability). Salehifar [50] takes similar research on cryptocurrency liquidity and price efficiency. The statistical results were consistent with Wang [59] findings. He also utilized Hurst exponent to check mean reversion of correspondent return series. The findings suggest high-liquid cryptocurrencies are improving in terms of market and price efficiency. Gholami et al., [27] however don't show a significant relationship between stock liquidity and information efficiency role of liquidity to predict default risks among TSE listed firms. At the best of our knowledge, the impact of stock liquidity on market efficiency (return predictability) has not been addressed in the Tehran Stock Exchange. The results of Hasani and Nabizadeh [30] research showed that there is a significant and positive relationship between stock liquidity and expected stock returns. This means that due to the relationship between risk and return in the stock market, by reducing (increasing) the stock liquidity risk, we will see changes in order to reduce (increase) the expected return on the shares of the companies under review. Farshadfar and Khalili [24] acknowledge that the combination of liquidity risk and momentum risk has a greater explanatory power in the relationship between risk and return and, consequently, the pricing of capital assets. Lansing et al., [39] examined the sources of excess return predictability in U.S. market. They show that the predictability of excess returns on risky assets can arise from only two sources: (1) stochastic volatility of fundamental variables, or (2) departures from rational expectations that give rise to predictable investor forecast errors and market inefficiency. While controlling for stochastic volatility, a variable which measures non-fundamental noise in the Treasury yield curve helps to predict 1-month-ahead excess stock returns, but only during sample periods that include the Great Recession [39]. Wen et al., [60] reports evidence of intraday return predictability, consisting of both intraday momentum and reversal, in the cryptocurrency market. Using high-frequency price data on Bitcoin from March 3, 2013, to May 31, 2020, it shows that the patterns of intraday return predictability change in the presence of large intraday price jumps, FOMC announcement release, liquidity levels, and the outbreak of the COVID-19. Intraday return predictability is also found in other actively traded cryptocurrencies such as Ethereum, Litecoin and Ripple [60].

Zhang et al., [63] examined the lead–lag relationship between industry portfolio returns and market returns in China, the largest emerging market, for the period 1993–2019. Using a bidirectional pairwise regression model, we found that the returns for banking and real estate not only predict market returns and returns for other industries but also predict industrial output growth. Since 2005, a shift in predictive ability from manufacturing to real estate has occurred, whereas banking has maintained consistent predictive power over the examined period. In the reverse direction, the stock market predicts the returns for mining and transportation [63]. Sun and Wen [55] find that cumulative abnormal returns adjusted by size, book-to-market, and momentum around the earnings announcement date (DGTW_CAR3 hereafter) significantly and positively predict stock returns in the 6-month period from May 2005 to October 2020 in the China's A-shares market [55]. Huang [36] argued that formation period return difference between past winners and losers, which he calls the *momentum gap*, negatively predicts momentum profits. He Document this for the U.S. stock market and find consistent results across 21 major international markets. A one-standard-deviation increase in the momentum gap predicts a 1.25% decrease in the monthly momentum return after controlling for existing predictors. This predictability extends up to 5 years for static momentum portfolios, consistent with time-varying investor biases [36]. The present study contributes to the literature in several ways. We examine connections between stock liquidity and earning predictability in an emerging market with contradictory degrees of efficiency. From a methodology standpoint, we use market-based signals (daily bid-ask quotes) to measure liquidity. Furthermore, market efficiency scholars have often applied one or two tests in each paper. We utilize a set of parallel tests to capture market efficiency.

3 Methodology

If the sale and purchase of stocks in the market is of high volume, the stock market is not dominated by the seller. In these situations, price offered by the seller per share (quoted ask price) or price seller would like to accept (quoted bid price) will be almost close. So, investors will not be forced to squander their money for quick sale. When the difference between proposed and requested (bid-ask) prices increase, market liquidity will be declined. If there is a higher gap between quoted bid-ask prices, market makers do not have incentive to make these securities marketable and consequently, liquidity is declined (1). Following Brogaard et al., [10], Fang et al., [22], Lipson & Mortal [40] and Hou & Moskowitz [35], we used effective spread to capture stock liquidity. This index embeds transaction cost, implicitly and is calculated as twice the difference between execution price and midpoint of the prevailing best bid-ask quote divided by midpoint of the prevailing best bid-ask quote as stated in Equation 1. The higher effective spread means less stock liquidity. The index is calculated daily for sample stock-companies.

$$\text{Effective Spread} = 2 \times \left(\frac{\text{close price} - \left(\frac{\text{best bid quote} + \text{best ask quote}}{2}\right)}{\frac{\text{best bid quote} + \text{best ask quote}}{2}} \right) \tag{1}$$

Following Wang [59] and Salehifar [50], we used daily stock price data of TSE listed companies to capture return as shown in Equation 2 below:

$$R_t = \ln(P_t) - \ln(P_{t-1}) \tag{2}$$

Where $\ln(P_t)$ stands for natural logarithm of the close price at day t. All data required to capture daily effective spreads and returns extracted from Tehran Stock Exchange Technology Management Company (TSETMC). This study covers a time horizon from December 2017 through December 2019 (two years). We considered each year as 52 weeks with five trading days. Then we subtracted 20 holidays from each to reach 240 trading days for 2018 and 2019. In order to ensure sufficient information to calculate liquidity and return variables, companies' stocks trading less than two-thirds of 240 trading days were excluded from the final sample. Therefore, the daily data of 116 firms with minimum of 160 trading days were used to form data model. We constructed a dated-regular frequency of time series with total 40128 stock-firm observations. After calculating daily effective-spreads and stock returns, we ranked observations based on liquidity measure, from most liquid (lowest effective spread) to lowest. Like Wang [59], we lied 40128 observations into three equal groups based on liquidity (Group1=high liquid, Group2=mid liquid, Group3=low liquid). Each liquidity group had its correspondent returns. Finally, the behavior of returns across different classes of stock liquidity was studied and compared. Our method involves testing the efficient market (earning unpredictability) hypothesis across different categories sorted for market liquidity. The more liquid category is expected to be identified by the lower return predictability (determined by a random walk and martingale process). Augmented Dickey Fouler (ADF) unit root statistics were used to ensure time series stationary as primary evidence for return predictability. To test hypothesis, the focus was made on examining the predictability of returns. Following Urquhart [57] and Wang [59], we applied same set of statistical tests for randomness checks.

- ✓ First of all, return autocorrelation was examined using Ljung-Box test [42]. The lower autocorrelation in return time series implied less predictability (efficient market).

✓ We used Bartels test [6] to test whether the three returns time series are independent or not. If the desired time series observations (return) are independent of each other, it can be concluded that the series is a random process (not predictable).

✓ Lo and MacKinlay's [43] variance ratio test (VAR) was employed to investigate if the standard deviation of returns scales by $\sqrt{T}$. To implement VAR test, we used wild-bootstrapped automatic model suggested by Kim [38]. This test shows stochasticity of returns time series.

✓ We utilized BDS [9] non-parametric test on serial dependence to check randomness of return series. Following Urquhart [57], embedding dimension from 2 to 6 were chosen and the corresponding probability values across different liquidity group specifications reported. A predictable return series is not martingale.

Finally, to check robustness of results, we calculated and reported the R/S Hurst exponent to examine long memory of returns [11]. Following rules are governing Hurst test results [59]:

R/S > 0.65 (time series is momentum)

0.65 > R/S > 0.45 (time series is fugitive)

0.45 > R/S (time series is mean reversion)

Momentum and mean reversion time series are not considered to follow random walk process [12].

3.1 Results and Discussion

Data collection and integration do not produce value and require advanced models for data analysis. The desirable conclusion is the result of an accurate analysis of the information gathered on the basis of the main research question. Table 1 shows descriptive statistics of return series across different liquidity groups. Mean of returns for high-liquid and low-liquid stocks was 0.1642% and 0.0692 % respectively. Investors taking more liquidity risk are not compensated with higher returns. These contrasts liquidity risk-premium supposal developed by Amihud & Mendelson [3] and Jacoby et al., [37]; but confirms Wang [59] findings from emerging and undeveloped financial markets. In addition, high-liquid stocks are linked with lower volatility of returns, which is in line with Amihud, as the degree of liquidity increases, the buyers and sellers' activity increases. This moves prices toward intrinsic not arbitrage trading values. So, the price and subsequently the return fluctuations decrease. The skewness and kurtosis coefficients show that at higher liquidity degrees, the return distribution as more symmetrical and closer to normal.

Table 1: Descriptive Statistics

Row	GROUP1	GROUP2	GROUP3
Mean	0.164274	0.068732	0.069255
Median	- 0.014957	- 0.064439	0.0000
Maximum	42.62922	53.72322	76.49476
Minimum	- 52.41862	- 35.15180	- 91.34753
Std. Dev.	2.048283	2.346410	4.481258
Skewness	- 2.553393	0.641050	- 3.395692
Kurtosis	101.0363	37.30147	87.47372
Observations	13376	13376	13376

Figure 1 and Figure 2 also graph the return scatter plots across different liquidity groups. As it can be seen, high-liquidity stock time series (group1) are more volatile and disperse than the low-liquidity stocks (group 3). Furthermore, low-liquidity stocks are almost bound to a certain range and stands for presence of long-term memory, implicitly.

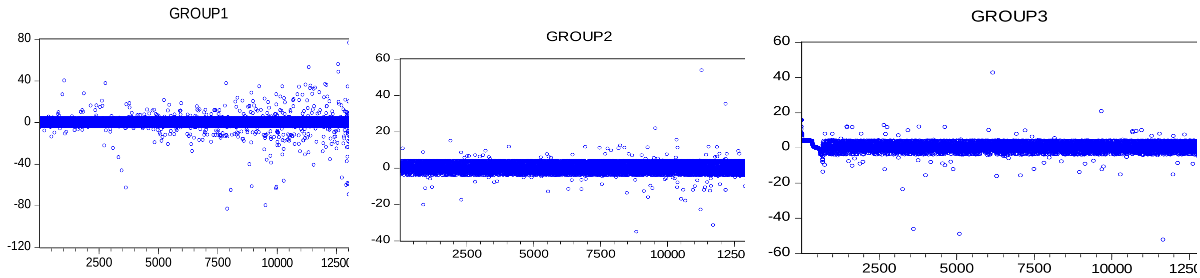

Fig. 1: Return Trends Across Liquidity Classes

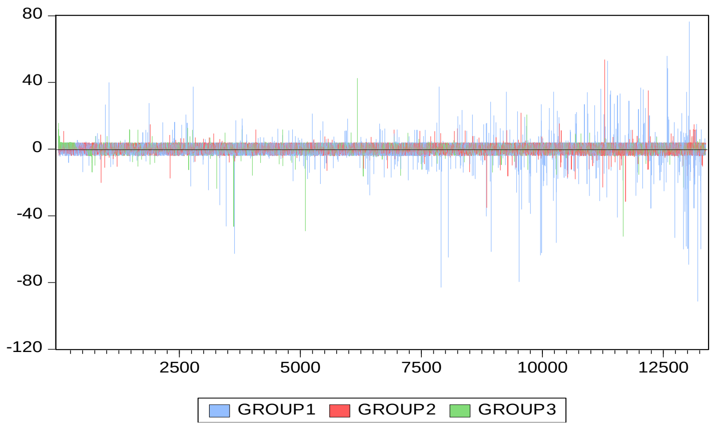

Fig. 2: Return Scatter Plot Across Liquidity Classes

Table 2: ADF Unit Root Test Results

GROUP 1				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-12.32354	0.0000
Test critical values:	1% level		-3.430667	
	5% level		-2.861564	
	10% level		-2.566824	
GROUP 2				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-113.4801	0.0001
Test critical values:	1% level		-3.430666	
	5% level		-2.861564	
	10% level		-2.566824	
GROUP 3				
			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-113.4801	0.0001
Test critical values:	1% level		-3.430666	
	5% level		-2.861564	
	10% level		-2.566824	

One of the parametric methods to study the predictability of a time series is to evaluate the stationarity. Stationarity is a constructive assumption in financial econometrics that constrains a series to fluctuate in a particular equilibrium range. If we can prove the with noise of daily stock returns series, we can judge they walks randomly. Table 2 provide ADF unit root test results across different liquidity groups. The null hypothesis stands for existence of unit roots in time series. Since the corresponding p-values are less than 5% significant level, the return time series are not with noise. This holds constant across different liquidity classes; return series are predictable and stock liquidity does not stimulate returns predictability. ADF provides primary evidence for rejecting underlying hypothesis. However, let's go through more robust statistical tests for further investigation.

We examine returns autocorrelations using Ljung-Box test. The Ljung-Box Q (LBQ) statistic tests the null hypothesis that autocorrelations up to lag k (20 in this case) equal zero. This stands for data values are random and independent up to a 20 lags). Table 3 shows high-liquid stock return series are not auto correlated; since the corresponding p-values are greater than 5% (except for firs lag that is significant at 99% confidence level).

Table 3: Ljung-Box Autocorrelation Test Results (High-Liquid Stocks)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.019	0.019	4.7551	0.029
		2	-0.00...	-0.00...	4.8988	0.086
		3	-0.01...	-0.01...	8.7717	0.032
		4	-0.00...	-0.00...	8.7932	0.066
		5	-0.00...	-0.00...	9.3219	0.097
		6	-0.00...	-0.00...	9.8132	0.133
		7	-0.00...	-0.00...	10.649	0.155
		8	-0.00...	-0.00...	11.555	0.172
		9	-0.00...	-0.00...	12.255	0.199
		1...	0.016	0.016	15.889	0.103
		1...	-0.00...	-0.00...	16.093	0.138
		1...	0.005	0.005	16.399	0.174
		1...	-0.00...	-0.00...	16.532	0.222
		1...	0.020	0.020	21.764	0.084
		1...	0.006	0.006	22.313	0.100
		1...	-0.01...	-0.01...	23.836	0.093
		1...	-0.00...	0.001	23.837	0.124
		1...	-0.01...	-0.01...	25.302	0.117
		1...	0.009	0.010	26.392	0.120
		2...	0.002	0.002	26.445	0.152

Table 4: Ljung-Box Autocorrelation Test Results (Mid-Liquid Stocks)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.170	0.170	387.98	0.000
		2	0.146	0.120	672.62	0.000
		3	0.146	0.108	956.01	0.000
		4	0.144	0.096	1233.6	0.000
		5	0.142	0.085	1503.0	0.000
		6	0.135	0.071	1746.2	0.000
		7	0.138	0.071	2002.9	0.000
		8	0.154	0.083	2320.0	0.000
		9	0.138	0.058	2575.9	0.000
		1...	0.142	0.060	2844.0	0.000
		1...	0.128	0.041	3062.8	0.000
		1...	0.131	0.044	3290.9	0.000
		1...	0.133	0.044	3527.1	0.000
		1...	0.133	0.043	3763.2	0.000
		1...	0.125	0.032	3971.1	0.000
		1...	0.126	0.033	4183.2	0.000
		1...	0.127	0.034	4400.6	0.000
		1...	0.128	0.034	4620.8	0.000
		1...	0.125	0.030	4831.0	0.000
		2...	0.112	0.015	5000.6	0.000

However, Table 4 and Table 5 reveal signs of autocorrelation for stocks returns with mid and low liquidity levels. Fama & French [18] argue part of the price shocks become permanent every month, and the rest of the shocks are gradually eliminated. Therefore, the autocorrelation test rests on the fact that the temporary segment of price shocks implies the ability to predict prices in future periods. Since autocorrelation breaches market efficiency, we can conclude stock high liquidity enhances market efficiency and diminishes return predictability. This supports from underlying hypothesis but is contradictory to ADF test results. This motivates us to go through supplementary tests of independence.

Table 5: Ljung-Box Autocorrelation Test Results (Low-Liquid Stocks)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.019	0.019	4.7758	0.029
		2	0.037	0.037	22.957	0.000
		3	0.011	0.010	24.674	0.000
		4	0.010	0.008	25.988	0.000
		5	-0.00...	-0.00...	26.018	0.000
		6	0.013	0.012	28.137	0.000
		7	-0.00...	-0.00...	28.139	0.000
		8	0.015	0.014	31.002	0.000
		9	0.005	0.005	31.406	0.000
		1...	0.026	0.024	40.310	0.000
		1...	0.014	0.013	43.055	0.000
		1...	0.022	0.019	49.285	0.000
		1...	-0.01...	-0.01...	50.519	0.000
		1...	0.010	0.008	51.823	0.000
		1...	-0.00...	-0.00...	52.785	0.000
		1...	0.008	0.007	53.728	0.000
		1...	0.020	0.020	59.100	0.000
		1...	-0.00...	-0.00...	59.116	0.000
		1...	-0.00...	-0.01...	60.184	0.000
		2...	0.001	-0.00...	60.193	0.000

Table 6 presents Bartel independence test results. The null hypothesis in this test implies randomness and independence of desired time series (return unpredictability). If the correspondent p-values of test exceed the desired significance level (5%), the return for high liquid TSE listed stocks is confirmed to be stochastic. It can be seen that all of p-values are less than 5% and the null hypothesis rejected. This stands for high dependence of return observations across different classes regardless of liquidity status. This contrasts efficient market notion. It also rejects underlying hypothesis we developed based on theoretical backgrounds.

Table 6: Bartel Test Results

GROUP 1				
Joint Tests		Value	df	Probability
Max |z| (at period 2)		49.27131	13375	0.0000
Wald (Chi-Square)		2438.515	4	0.0000
Individual Tests				
Period	Var. Ratio	Std. Error	Z-Statistic	Probability
2	0.573963	0.008647	-49.27131	0.0000
4	0.329990	0.016177	-41.41849	0.0000
8	0.211431	0.025577	-30.83065	0.0000
16	0.153892	0.038060	-22.23062	0.0000
GROUP 2				
Joint Tests		Value	df	Probability
Max |z| (at period 2)		53.08607	13375	0.0000
Wald (Chi-Square)		2819.423	4	0.0000
Individual Tests				
Period	Var. Ratio	Std. Error	Z-Statistic	Probability
2	0.540978	0.008647	-53.08607	0.0000
4	0.300717	0.016177	-43.22808	0.0000
8	0.175528	0.025577	-32.23432	0.0000
16	0.111448	0.038060	-23.34581	0.0000
GROUP 3				
Joint Tests		Value	df	Probability
Max |z| (at period 2)		54.07564	13375	0.0000
Wald (Chi-Square)		2924.696	4	0.0000
Individual Tests				
Period	Var. Ratio	Std. Error	Z-Statistic	Probability
2	0.532421	0.008647	-54.07564	0.0000

Table 6: Bartel Test Results

4	0.291894	0.016177	-43.77349	0.0000
8	0.170873	0.025577	-32.41635	0.0000
16	0.107478	0.038060	-23.45013	0.0000

Tales 7 and 8 also test randomness of return across different classes of stock liquidity using variance ratio test and BDS test, respectively. The before mentioned results hold to be constants over both two test. According to VAR test, variance ratio should be equal to one when the conditions of log returns being serially uncorrelated and homoscedastic are satisfied. If the null hypothesis cannot be rejected, then it implies that the two assumptions are consistent with the reality. Conversely, a rejection of null hypothesis means at least one of the two mentioned assumptions is inconsistent with reality. Table 7 reports VAR as well as corresponding p-values across different liquidity quartiles. As the VAR are economically insignificant and vis-à-vis p-values are less than 5%, we conclude neither high liquid stocks return nor low liquid ones are uncorrelated and homoscedastic.

Table 7: Variance Ratio Test Results

GROUP 1				
Joint Tests		Value	df	Probability
Max |z| (at period 4)*		9.385506	13375	0.0000
Individual Tests				
Period	Var. Ratio	Std. Error	Z-Statistic	Probability
2	0.514079	0.052394	-9.274437	0.0000
4	0.256933	0.079172	-9.385506	0.0000
8	0.126618	0.093812	-9.309883	0.0000
16	0.065187	0.103575	-9.025480	0.0000
GROUP 2				
Joint Tests		Value	df	Probability
Max |z| (at period 2)*		16.82254	13375	0.0000
Individual Tests				
Period	Var. Ratio	Std. Error	Z-Statistic	Probability
2	0.511354	0.029047	-16.82254	0.0000
4	0.255230	0.044958	-16.56589	0.0000
8	0.128539	0.056252	-15.49209	0.0000
16	0.064472	0.066907	-13.98251	0.0000
GROUP 3				
Joint Tests		Value	df	Probability
Max |z| (at period 2)*		12.21934	13375	0.0000
Individual Tests				
Period	Var. Ratio	Std. Error	Z-Statistic	Probability
2	0.490904	0.041663	-12.21934	0.0000
4	0.252380	0.063762	-11.72507	0.0000
8	0.125647	0.077237	-11.32041	0.0000
16	0.063290	0.089710	-10.44151	0.0000

This also implies there is no connection between stock liquidity and earning predictability (market efficiency), rejecting research core hypothesis. This is also the case for BDS independence test results. BDS test examines the “spatial dependence” of the return series. To run this test, the return series is embedded in different space and the dependence of return is examined by counting "near" points. The BDS test null hypothesis indicates underlying series is martingale and stochastic. The BDS test one of the portmanteau set of test for time based dependence in a time series. This test can be utilized for testing against a diversity of possible aberrations from independence including linear dependence, non-linear dependence, or even chaos.

According Table 8, to BDS test results, as the corresponding p-values are less than 5% significance level, we can reject null hypothesis. However, the logarithmic daily returns on assets don't vary across different liquidity classes. This persuades us to reject underlying hypothesis.

Table 8: BDS Test Results

GROUP 1				
Dimension	BDS Statistic	Std. Error	Z-Statistic	Prob.
2	0.025869	0.000950	27.23890	0.0000
3	0.041275	0.001513	27.28549	0.0000
4	0.047001	0.001806	26.02314	0.0000
5	0.046603	0.001888	24.68530	0.0000
6	0.042453	0.001826	23.24803	0.0000
GROUP 2				
Dimension	BDS Statistic	Std. Error	Z-Statistic	Prob.
2	0.004238	0.000634	6.682148	0.0000
3	0.006487	0.001002	6.471307	0.0000
4	0.008678	0.001187	7.311119	0.0000
5	0.009731	0.001230	7.909807	0.0000
6	0.009754	0.001180	8.268626	0.0000
GROUP 3				
Dimension	BDS Statistic	Std. Error	Z-Statistic	Prob.
2	0.003525	0.000552	6.383747	0.0000
3	0.006944	0.000870	7.985671	0.0000
4	0.008838	0.001026	8.618060	0.0000
5	0.009964	0.001059	9.412410	0.0000
6	0.010131	0.001011	10.02218	0.0000

So far, unit root, autocorrelation, independence and random walk tests of time series were applied to investigate whether the stock liquidity contributes to predictability of returns as an indicator of information efficiency in TSE listed firms-stock observations. The results (except for Ljung-Box test) don't provide signs of connection between stock liquidity and return predictability. To check the robustness and decide on hypothesis validity in TSE, we apply the Hurst exponent to ensure the predictability of returns regardless of liquidity characteristic. The results are presented in Table 9. Hurst exponent is used to measure long-term memory over a series of time periods, in which the memory of a series (like return) is defined based on observing its limit events over a given time interval. If the Hurst exponent takes values greater than 0.65, it can be concluded that the desired time series is momentum. As the same way, values less than 0.45 stands for mean reversion. If the test exponent lies between 0.65 and 0.45, the considered time series is fugitive and walks randomly. Table 9 show the Hurst exponents for different classes of stock liquidity.

Table 9: Hurst Exponent Test Results

Series	N	Hurst Exponent	H-L	H-U
GROUP 1	13376	0.40564	0.37809	0.451914
GROUP 2	13376	0.38195	0.38255	0.417248
GROUP 3	13376	0.42001	0.41621	0.40737

Given that the Hurst exponent is less than 0.45 for all of return time series regardless of liquidity classes, we conclude that the returns time series are mean reversed. This provides signs of predictability and violates the efficient market notion. The Hurst test results also don't show any connections between stock liquidity and return predictability. To sum up with the results and test liquidity associations with predictability of return, we draw Table 10. It summarizes the empirical findings from different tests for the high-liquid class of stocks.

Table 10. Summary of Test Results

Test	Nature	Test results	Main hypothesis
ADF	Stationarity	Return series is white noise	Reject
Ljung-Box	Autocorrelation	Return series is not autocorrelated for 20 lags	Confirmed
Bartel	Independence	Return series observations are not independence	Reject
VAR	Stochasticity	Return series is not stochastic	Reject
BDS	Random walk	Return series does not follow random walk process	Reject
Hurst	Long-term memory	Return series is mean reversion	Reject

We conclude that different liquidity classes reject the null hypothesis of randomness in all tests. The average p-values for each test is not affected by liquidity degree of stock suggesting no connectivity between liquidity, return unpredictability and market efficiency. Furthermore, the Hurst exponent robustness check also provides evidence of mean reversion phenomenon in both liquid and illiquid classes of stocks which does not confirm research hypothesis to be prevalent for most developed markets.

5 Conclusion

Generally speaking, price/return stationarity, random walk, non-autocorrelation non- independence, as well as lack of long-term memory, momentum and mean reversion of return are the most important evidence of an efficient market. The efficient market hypothesis is also based on the premise that a market is considered to be efficient where prices and returns pursue a stochastic process and are unpredictable. The stock prices in such a market reflect the facts about stocks (not past events). Literature of efficient markets provides evidence for connections of liquidity and earning predictability. We examined the associations between stock liquidity (measured in terms of order flows) and market efficiency (measured in terms of return predictability) across 40128 stock observations in three classes of liquidity. The descriptive statistics didn't provide signs of an illiquidity premium among TSE listed firms, suggesting TSE investors are not necessarily demanding a risk premium for holding illiquid stocks. According to empirical results, liquidity does not affect predictability of returns and information efficiency in TSE.The unit root test results show that the time series of returns in all three liquidity classes are recurring or stationer and this feature is constant among different classes of liquidity. In other words, stock returns in different classes (regardless of the degree of liquidity) are predictable and stock liquidity does not make returns unpredictable.

Then, the time series correlation of returns in different classes of stock liquidity was tested separately using the Ljung-Box and the Bartel autocorrelation test, and then the average results were reported. The results showed that when using Ljung-Box autocorrelation, the time series of returns in the high liquidity class is not auto-correlated and has independence, which indicates the confirmation of the underlying hypothesis. Fama and French [18] argue that some price shocks become permanent each month and other shocks are gradually eliminated. Thus, the autocorrelation test is based on the fact that the temporary part of price shocks indicates the ability to predict prices in future periods. Since autocorrelation violates market efficiency, it can be concluded that high liquidity of stocks increases market efficiency and reduces the ability to predict returns. However, the findings of Bartel's correlation test violated the results of the Ljung-Box method. Then, two statistical, BDS and variance ratio tests (VAR) were utilized. The purpose of both was to evaluate the independence of returns observations in different classes of liquidity. Since the VARs as well as the corresponding mean levels of significance obtained for the BDS test statistics were statistically insignificant, it was concluded that neither the high liquid stock returns nor the low liquid stocks are random and independent of either time series. Finally, the Hurst statistic / index was used to examine the existence of long-term memory in the time series of returns in different liquidity classes and to ensure the results obtained in the previous sections. indicate the existence of "mean reversion" feature of the time series in different classes of liquidity, which violates the efficient market hypothesis and the basic hypothesis of this study.The results are inconsistent with Chordia et al., [13] and Fang [22] findings. Furthermore, Hurst exponent shows evidence of mean reversion in both liquid and illiquid stocks (< 0.45) which contrasts the findings of Urquhart [57] to be prevalent for most liquid financial assets. However, in the higher liquidity quintiles the Hurst exponent is also mean reversed not random walk showing inefficiency of TSE as an emerging market relative to Chordia et al., [13], Wang [59] and Salehifar [50] findings. One reason for this is that traders don't tend to eliminate the predictability of return through arbitrage trading; this diminishes market efficiency. Anomalies such as mean reversion, dependence, etc. represent trends in price and return that contradict the information efficiency notions. In case of TSE as other emerging markets, due to the small number of traders (the need for more trading activity) and low market making activities, both the cost of trading increases and the reaction to stock price information is delayed, resulting in predictability of price /return. According to the results and the theoretical foundations, one of the most important factors in eliminating the signs of predicting stock returns and strengthening the information efficiency of the capital market is arbitrage transactions.

It is suggested to policy makers in the stock exchange to provide the necessary infrastructure to strengthen arbitrage transactions. One of these infrastructures is adjusting or eliminating the range of stock price fluctuations (price domain). Without the price domain, prices move towards real prices. Also, due to the high cost of transactions in TSE, thinking about measures to reduce transaction costs and increase market transparency will increase liquidity in the capital market and increase the mobility of actors. Another proposed way to strengthen the efficiency of the capital market and reduce the predictability of stock returns is to increase trading activities in the capital market. Utilizing capacities such as effective market making, strengthening the culture of institutional shareholding, encouraging legal entities (portfolio companies, investment companies, investment funds, insurance companies, banks and credit institutions) to be more active in the capital market can be traced more seriously. Put on the agenda; In the absence of market making activities and a large number of active traders, the cost of trading increases and reactions to the stock price of companies are delayed, which is a serious obstacle to the efficiency of the capital market and unpredictability of returns.There are some limitations to this research that should be considered in generalizing the results. For example, some companies have not any stock transactions for a long time due to the symbol being closed; therefore, such companies were excluded from the sample. Also, the existence of price fluctuation range causes prices to reach the desired price range of the market and finally less quickly. Existence of excess demand over supply and vice versa, existence of excess supply over demand along with the existence of price fluctuation range reduces and sometimes stops trading. This aspect of stock liquidity is related to the infrastructure of the stock market and should be considered in the use of research results. This study also uses daily data from quotes and stock returns, and caution should be exercised in extending the results to other time intervals. Due to the above limitations, reviewing the hypotheses of this research for longer time intervals and also by industry (if there is a sufficient number of samples) is one of the topics that are suggested for future research. In this study, the effective difference index of short-sell quotes was used to measure the liquidity of companies' stocks. Given that there may be other indicators for measuring liquidity or examining the predictability of companies' stock returns, conducting the present study by considering other liquidity indicators (such as Amihud, zero return, etc.) and other test methods of time series (ARCH and GARCH) and comparison of the obtained results with the findings of this research is one of the topics that are suggested to interested researchers.

References

[1] Acharya, VV., Pedersen, LH., *Asset pricing with liquidity risk*, Journal of financial Economics, 2005, **77**(2), P.375-410. Doi:10.1016/j.jfineco.2004.06.007

[2] Ahadi Sarkani, U., Ghasempour, M., *Evaluation the Effects of Monetary and Fiscal Policy and Iindustry Growth on Changes of Tehran Security Exchange Index*, Journal of Investment Knowledge, 2017, **6**(22), P.49-64. (In Persian).

[3] Amihud, Y., Mendelson, H., *Asset pricing and the bid-ask spread*, Journal of financial Economics, 1986, **17**(2), P. 223-49. Doi:10.1016/0304-405X(86)90065-6

[4] Bahar Moghaddam, M., Hosseini Nasab, H., Raisi, H., Effect *of Stock Liquidity on Stock Price Informativeness and Accruals-Based Earnings Management in Companies Listed in Tehran Stock Exchange*, Financial Accounting Research, 2016, **7**(4), P.39-56. (In Persian).

[5] Baker, M., Stein, JC., Wurgler, J., When *does the market matter? Stock prices and the investment of equity-dependent firms*, The quarterly journal of economics, 2003, **118**(3), P.969-1005. Doi:10.1162/00335530360698478

[6] Bartels, R., *The rank version of von Neumann's ratio test for randomness*, Journal of the American Statistical Association,1982, **77**(377), P.6-40. Doi:10.2307/2287767

[7] Boehmer, E., Jones, CM., Zhang, X., *Which shorts are informed?* The Journal of Finance, 2008, **63**(2), P.491-527. Doi:10.1111/j.1540-6261.2008.01324.x

[8] Bond, P., Edmans, A., Goldstein, I. *The real effects of financial markets*, Annu. Rev. Financ. Econ, 2012, **4**(1), P.339-360. Doi:10.2139/ssrn.1976347.

[9] Brock, WA., Dechert, WD., *Non-linear dynamical systems: instability and chaos in economics*, Handbook of mathematical economics, 1991, **4**(1), P.2209-2235 Doi:10.1016/S1573-4382(05)80015-3

[10] Brogaard, J., Li, D., Xia, Y., *Stock liquidity and default risk*, Journal of Financial Economics, 2017, **124**(3), P.486-502. Doi: 10.1016/j.jfineco.2017.03.003

[11] Cajueiro, DO., Tabak, BM., *The Hurst exponent over time: testing the assertion that emerging markets are becoming more efficient*, Physica A: statistical mechanics and its applications, 2004, **336**(3), P.521-537. Doi:10.1016/j.physa.2003.12.031

[12] Carbone, A., Castelli, G., Stanley, HE., *Time-dependent Hurst exponent in financial time series*, Physica A, Statistical Mechanics and its Applications, 2004, **344**(2), P.267-271. Doi:10.1016/j.physa.2004.06.130

[13] Chordia, T., Roll, R., Subrahmanyam, A., *Liquidity and market efficiency*, Journal of financial Economics, 2008, **87**(2), P.249-268. Doi:10.1016/j.jfineco.2007.03.005

[14] Christiansen, C., *Mean reversion in US and international short rates*,The North American Journal of Economics and Finance, 2010, **21**(3), P.286-296. Doi:10.1016/j.najef.2009.08.002

[15] Cooper, SK., Groth, JC., Avera, WE. *Liquidity, exchange listing, and common stock performance*, Journal of Economics and Business, 1985, **37**(1), P.19-33. Doi:10.1016/0148-6195(85)90003-7

[16] Edmans, A., *Blockholder trading, market efficiency, and managerial myopia*, The Journal of Finance. 2009, **64**(6), P. 2481-2513. Doi:10.1111/j.1540-6261.2009.01508.x

[17] Erza, A., Seifi, F., *The Impact of Financial Risk on the Efficiency in the Tehran Stock Exchange Companies*,Financial Knowledge of Securities Analysis, 2020, **13**(45), P. 1-13. (In Persian)

[18] Fama, EF., French, KR., *Financing decisions: who issues stock?* Journal of financial economics. 2005, **76**(3), P.549-582. Doi: 10.1016/j.jfineco.2004.10.003

[19] Fama, EF., *Efficient capital markets: A review of theory and empirical work*, The journal of Finance. 1970, **25**(2), P.383-417. Doi:10.2307/2325486

[20] Fama, EF., *Efficient market hypothesis*, Diss. PhD Thesis, Ph. D. dissertation, 1960.

[21] Fama, EF., *The behavior of stock-market prices*, The journal of Business, 1965, **38**(1), P.105-134.

[22] Fang, J., *Stock liquidity, price informativeness, and accruals-based earnings management*, 2012.

[23] Farshadfar, Z., Prokopczuk. M., *Improving Stock Return Forecasting by Deep Learning Algorithm*, Advances in Mathematical Finance and Applications, 2019, 1, **4**(3), P.1-13.
Doi: 10.22034/AMFA.2019.584494.1173

[24] Farshadfar, Z., Khalili Eraghi, M., *Study the Effect of Stock Liquidity on Excess Return with Five Factors Arbitrage Pricing Model*, Financial Knowledge of Securities Analysis, 2016, **9**(29), P.97-109. (In Persian)

[25] Gerken, WC., *Blockholder ownership and corporate control: the role of liquidity*, The Quarterly Journal of Finance. 2014, **4**(01):1450003. Doi:10.1142/S2010139214500037

[26] Ghojavand, S., Ghojavand, Z., Hashemi, A., *Effect of Different Levels of Liquidity Measures on the Premium Stock Returns Using the Four-Factor Model of Fama and French*, Journal of Asset Management and Financing, 2013, **1**(2), P.69-86. (In Persian).

[27] Gholami, R., Narrei B., Azizi, P., *Effects of Turnover on Stock Price Delay in Companies Listed in Tehran Stock Exchange*, Journal of Accounting Knowledge, 2019, **10**(3), P.33-67. (In Persian).

[28] Glosten, LR., Milgrom, PR. *Bid, ask and transaction prices in a specialist market with heterogeneously informed traders*, Journal of financial economics. 1985, **14**(1), P.71-100. Doi:10.1016/0304-405X(85)90044-3

[29] Grossman, SJ., Stiglitz, JE. *On the impossibility of informationally efficient markets*, The American economic review, 1980, **70**(3), P.393-408.

[30] Hasani, M., Nabizadeh, N., *Evidence of the effect of illiquidity of stocks on the expected returns of stocks*, 2016. (In Persian).

[31] Hayek, FA., *The use of knowledge in society*, The American economic review, 1945, **35**(4), P.519-530.

[32] Hirshleifer, D., Teoh, SH., Yu, JJ. *Short arbitrage, return asymmetry, and the accrual anomaly*, The Review of Financial Studies, 2011, **24**(7), P.2429-2461. Doi:10.1093/rfs/hhr012

[33] Holden, CW., Jacobsen, SE., Subrahmanyam, A., *The empirical analysis of liquidity*, Foundations and Trends in Finance, 2014, **8(1)**, P.263-365. Doi:10.2139/ssrn.2402215

[34] Holmström, B., Tirole, J., *Market liquidity and performance monitoring*, Journal of Political economy, 1993, **101**(4), P.678-709. Doi:10.1086/261893

[35] Hou, K., Moskowitz, TJ., *Market frictions, price delay, and the cross-section of expected returns*, The Review of Financial Studies, 2005, **18**(3), P.981-1020. Doi:10.1093/rfs/hhi023

[36] Huang, S., *The momentum gap and return predictability*, The Review of Financial Studies, 2022, 3303-3336. Doi:10.1093/rfs/hhab093

[37] Jacoby, G., Fowler, DJ., Gottesman, AA., *The capital asset pricing model and the liquidity effect: A theoretical approach*, Journal of Financial Markets, 2000, **3**(1), P.69-81. Doi:10.1016/S1386-4181(99)00013-0

[38] Kim, JH., *Automatic variance ratio test under conditional heteroscedasticity*, Finance Research Letters, 2009, **6**(3), P.179-185. Doi:10.1016/j.frl.2009.04.003

[39] Lansing, KJ., LeRoy, SF., Ma J. *Examining the sources of excess return predictability: Stochastic volatility or market inefficiency?* Journal of Economic Behavior & Organization, 2022, P.50-72. Doi:10.1016/j.jebo.2022.01.028

[40] Izadikhah, M., *A Fuzzy Goal Programming Based Procedure for Machine Tool Selection*, 2015, **28**(1), P. 361-372, Doi: 10.3233/IFS-141311

[41] Izadikhah, M., *Financial Assessment of Banks and Financial Institutes in Stock Exchange by Means of an Enhanced Two stage DEA Model*. *Advances in Mathematical Finance and Applications*, 2021, **6**(2), P. 207-232. Doi: 10.22034/amfa.2020.1910507.1491

[42] Lipson, ML., Mortal, S., *Liquidity and capital structure*. Journal of financial markets, 2009, **12**(4), P.611-644. Doi:10.1016/j.finmar.2009.04.002.

[43] Liu, W., *A liquidity-augmented capital asset pricing model*. Journal of financial Economics, 2006, **82**(3), P.631-671. Doi:10.1016/j.jfineco.2005.10.001.

[44] Ljung, GM., Box, GE. *On a measure of lack of fit in time series models*. Biometrika, 1978, **65**(2), P.297-303. Doi:10.1093/biomet/65.2.297.

[45] Lo, AW., MacKinlay, AC., *Stock market prices do not follow random walks: Evidence from a simple specification test*, The review of financial studies, 1988, **1**(1), P.41-66. Doi:10.1093/rfs/1.1.41.

[46] Luo, Y., *Do insiders learn from outsiders? Evidence from mergers and acquisitions*, The Journal of Finance,2005, **60**(4), P.1951-1982.

[47] Ozdenoren, E., Yuan, K. *Feedback effects and asset prices*, The journal of finance,2008, **63**(4), P.1939-1975. Doi:10.1111/j.1540-6261.2008.01378.x.

[48] Pástor, Ľ., Stambaugh, RF. *Liquidity risk and expected stock returns*, Journal of Political economy, 2003, **111**(3), P.642-85. Doi:10.1086/374184.

[49] Piotroski, JD., *Value investing: The use of historical financial statement information to separate winners from loser*, Journal of Accounting Research, 2000, **1886**(13), P.1-41, Doi:10.1016/S2077-70024-6.

[50] Raei, R., Eivazlu, R., Abbaszadeh Asl., A., *Investigation on relation between information asymmetry and liquidity via market microstructures model in Tehran Stock Exchange*, Financial Knowledge of Securities Analysis, 2017, **10**(34), P.13.24. (In Persian)

[51] Rahmani, A., Hosseini, S., Rezapour, N., *Institutional Ownership and Stock Liquidity: Evidence from Iran*, Accounting and Auditing Review, 2010, **17**(3), P.39-54. (In Persian)

[52] Salehifar, M., Rahnamay Roodposhti, F., Chaharmahali, H., *The Application of Ecology Theories in Finance*, Journal of Investment Knowledge, 2019, **8**(29), P.137-58. (In Persian)

[53] Samadi, R., Ezazi, M., Tehrani, R., Roshan, SA., Nabi Shahiki Tash, M. *Approach of Maximal overlap discrete wavelet transforms to stock return in the Iran capital market,* Advances in Mathematical Finance and Applications, 2022. (In Persian).

[54] Sarin, A., Shastri, K., Shastri, K., *Ownership structure and stock market liquidity*, Available at SSRN 02652.

[55] Soheili, K., Amirian, S., *Investigating the relationship between liquidity and stock return rate with free floating shares in Tehran Stock Exchange*, Macroeconomic Research Journal, 2013**, 9**(18), P.1-13. (In Persian)

[56] Subrahmanyam, A., Titman, S., *Feedback from stock prices to cash flows*, The Journal of Finance, 2001, **56**(6), P.2389-2413. Doi:10.1111/0022-1082.00409

[57] Sun, PW., Wen, Z., *Stock return predictability of the cumulative abnormal returns around the earnings announcement date*, Evidence from China. International Review of Finance, 2022, Doi:10.1111/irfi.12380

[58] Taherinia, M., Rashidi Baghi, M., *Prediction the Return Fluctuations with Artificial Neural Networks' Approach*, Advances in Mathematical Finance and Applications, 2019, **4**(2), P.103-114.
Doi: 10.22034/amfa.2019.580643.1149.

[59] Urquhart, A. *The inefficiency of Bitcoin. Economics Letters*, 2016, **148**(1), P.80-82.
Doi:10.1016/j.econlet.2016.09.019

[60] Vassalou, M., Xing, Y., *Default risk in equity returns*, The journal of finance, 2004, **59**(2), P.831-868. Doi:10.1111/j.1540-6261.2004.00650.x

[61] Wang, WC., *Liquidity and market efficiency in cryptocurrencies*, Economics, Letters, 2018, **168**(1), P.21-24. Doi:10.1016/j.econlet.2018.04.003

[62] Wen, Z., Bouri, E., Xu, Y., Zhao, Y., *Intraday return predictability in the cryptocurrency markets: momentum, reversal, or both*, The North American Journal of Economics and Finance, 2022, **8**(2), P.101733-48.
Doi: 10.1016/j.najef.2022.101733

[63] Wilson, R., *Information, efficiency, and the core of an economy. Econometrica*, Journal of the Econometric Society, 1978, P.807-16. Doi:10.2307/1909750

[64] Yahyazadeh Far, M., Shams, S., Larimi, S., *The Relationship between liquidity and stocks return in Tehran Stock Exchange,* Financial Research Journal, 2010, **12**(29), P.111-128. (In Persian)

[65] Zhang, Y., Tse, T., Zhang, G., *Return predictability between industries and the stock market in China*, Pacific Economic Review, 2022. Doi:10.1111/1468-0106.12379.

[66] Zamani, S., Zanjirdar, M., Lalbar, A. *The effect of information disclosure on market reaction with meta-analysis approach*, Advances in Mathematical Finance and Applications, 2022, **7**(3), P. 629-644.
Doi: 10.22034/amfa.2021.1937478.1625

[67] Zanjirdar, M., *Overview of Portfolio Optimization Models. Advances in Mathematical Finance and Applications,* 2020, **5**(4), P.419-435. Doi: 10.22034/amfa.2020.674941.

[68] Zanjirdar, M., Kasbi, P., Madahi, Z., *Investigating the effect of adjusted DuPont ratio and its componentson investor & quot; s decisions in short and long term*, Management Science Letters, 2014, **4**(3), P.591-596.
Doi: 10.5267/j.msl.2014.1.003