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Article

Tehran Stock Market efficiency: A quantile autoregression approach

Masoud Alizadeh Chamazkoti, Mehdi Fathabadi*, Saleh Ghavidel Doostkouei, Mahmood Mahmoodzadeh

Department of Economics, Firoozkooh Branch, Islamic Azad Universsity, Firoozkooh 3981838381, Iran
*** Corresponding author:** Mehdi Fathabadi, Mehdi_fa88@yahoo.com

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Abstract: The purpose of this paper is to evaluate the price efficiency of the Tehran Stock Market. For this aim, we used daily stock prices of 30 large companies on the Stock Exchange. In the first stage, a unit root test with the endogenous break and without a structural break was performed using augmented dickey-fuller test (ADF) tests and Phillips-perron (PP) tests. The results indicate that the price of 9 companies has a random walk process with intercept and 21 companies follow a random walk without intercept and trend component process which is known as the pure random walk process. Thus, considering the ADF and PP tests, most companies' stock prices are efficient. Quantile autoregression results in the second stage show that the stock prices in the middle price deciles have weak efficiency, but in the lower and upper price deciles, the stock price does not follow the weak efficiency conditions. So, if the stock price deviates (up or down) from the long-term mean, the market becomes inefficient, but when the stock price is at the median level, the market is efficient. The general conclusion is that median prices are the long-term average prices that change over time, and stock prices tend to move toward that price.

Keywords: market efficiency; quantile autoregression; random walk; Tehran Stock Market
JEL Classification: C21; C22; G14

1. Introduction

Economic and financial analysts have sought to find ways to predict macroeconomic and financial variables, including stock prices, since the 1950s. Stock prices reflect the future economic prospects of a firm. Thus, it is possible to plan for the future conditions of the firm by achieving the pattern of stock price changes. Testing a hypothesis, Kendall [1] noticed that stock prices seemed to move randomly over time and there is no pattern for predicting stock price changes. The stock market does not follow any rules and is irregular according to the results of the analysis. The irregularity in stock price changes is not due to irrationality but to market performance or market efficiency according to other researchers [2–5].

It is important for stock market investors and analysts to understand how the stock price process works. There are two types of processes in the econometric literature on time series, including stochastic processes (unit root) and stationary processes or mean-reversion processes. If stock prices follow the mean reversion process, with each shock, the price level will revert to its long-term trend over time. In other words, the effect of shocks on stationary time series is always temporary and these effects disappear over time and the series returns to its long-run average. In this case, it is possible to predict future changes in stock prices based on past stock behavior. On the contrary, stochastic volatility assumes that the price volatility of stock varies and is not constant over time; then, any kind of a shock to the price will be permanent. This means that the occurrence of shocks will have a permanent effect on the time series, and this effect is directly reflected in the prediction of the variable. Therefore, it is not possible to predict future stock prices based on past behaviors, which means that the market is efficient [6].

"Capital market efficiency" means "information efficiency". Though the efficient market hypothesis theorizes the market is generally efficient, the theory is offered in three different versions: weak, semi-strong, and strong. The weak form suggests that it is not possible to gain additional returns (other than luck) using historical information. If you have access to the general information of the company, you can get additional returns in this type of market. The semi-strong form submits that because public information is part of a stock's current price, investors cannot utilize either technical or fundamental analysis, though information not available to the public can help investors. The strong form version states that public and not public information, other than luck, can't give an investor an advantage in the market to gain additional returns.

There are at least two reasons why evaluating the efficient market hypothesis remains crucial [7]. Firstly, according to Bose [8], the significant interplay between the stock market and the real economy underscores its pivotal role in shaping economic policies. Secondly, Mauro [9] suggests that the rapid availability of stock market prices positions it as a valuable leading indicator for predicting economic growth. Furthermore, identifying which stock price changes, not explained by fundamentals, actually influence output raises pertinent policy issues, particularly relevant for emerging markets.

This paper aims to examine the weak efficiency in which the nature of stock price change is following the random walk model [2]. If this type of efficiency exists, stock prices would be very unpredictable and thus would follow a random walk. The randomness of stock prices is the logical result of keen competition between investors to discern new information so that they can decide whether to buy, sell or hold stock before the market is aware of it and reacts to the changes.

Many studies have examined the efficiency of stock prices, predominantly using parametric approaches. These include independence tests, variance ratio tests, various time series and panel unit root tests, autoregressive models, GARCH models, and Markov switching models. A few studies have also utilized quantile models, which have the capability to measure efficiency dynamics and determine the degree of efficiency at different price levels.

Additionally, it is important to clarify that weak efficiency implies that stock prices follow a random walk process. However, a pure random walk excludes both intercept and trend components. The presence of these components in a random walk model suggests a trend or additional return, which contradicts the concept of efficiency. This nuance is often overlooked in many studies, casting doubt on their results.

Random data entry causes price changes to be random (sometimes positive and sometimes negative). Price changes are the result of investors making new decisions about buying or selling stock relying on re-evaluating the future status of stocks. The paper investigated the weak efficiency of stock prices of 30 large companies registered at the Tehran stock exchange using the unit root quantile autoregression approach. The remainder of the paper is structured as follows. Section 2 presents the model. Section

3 displays the data. Section 4 is devoted to the empirical results while section 5 discusses them and concludes.

2. Literature review

When discussing market efficiency, it specifically refers to the relationship between stock prices and information. The important question is how quickly the market can obtain and adjust prices based on new information about a particular company. If prices react quickly and accurately to all important and effective information, the market can be considered relatively efficient. However, if this information reaches the market slowly and investors cannot quickly analyze and react to it, prices are likely to deviate from their true value. Such a market is relatively inefficient or lacks efficiency [10]. This raises the question: since investors do not receive clear and complete information about securities or specific stocks, how can the market ensure that security prices reflect all important and effective information? The answer is that prices are not determined by the consensus of all investors but by those actively present in the stock market. The market comprises expert analysts and highly knowledgeable traders who spend most of their time seeking out securities they believe are mispriced based on their information.

Investigating efficiency in the stock market is crucial. Paradoxically, the market is efficient if enough knowledgeable analysts believe it is not. This apparent contradiction is clear: careful investor analysis makes security prices reflect the true value of investments. However, if people believe the market is efficient, they see no point in searching for mispriced securities and will not incur the cost of acquiring new information. Consequently, security prices do not incorporate newly released information promptly, and prices adjust slowly, leading to an inefficient market. Conversely, if investors believe the market is inefficient, they find opportunities for abnormal returns, rush to new information, adjust prices accordingly, and inadvertently contribute to market efficiency, albeit poor performance [11]. In the context of weak efficiency, stock price changes follow a random walk model [2], meaning they are random and unpredictable. This randomness results from intelligent competition among investors to discover new information and make decisions before the market reacts. As information enters randomly, price changes are also random—sometimes positive, sometimes negative [2]. However, these changes are due to investors re-evaluating the future state of stocks and making new buy or sell decisions.

Fama [2] believed that an efficient market is one where stock prices fully reflect all available information, eliminating the possibility of making unusual profits, achievable through the random walk model. The question then arises: which random walk model can confirm the efficient market hypothesis? In the pure random walk model, without a constant component and trend, the expected mean is constant, indicating no trend in the mean. However, in random walk models with trend and constant components, a time trend is observed in the expected mean, and the mean is not constant. Additionally, in all three models, the variance is not constant and shows a time trend. If a trend exists in these models (except for the pure random walk model), it might imply additional returns, thus market inefficiency. If it can be proven that a stock follows a random walk model with a constant component, one could expect to earn returns equivalent to the trend coefficient daily, indicating inefficiency. Fama [2] implies that confirming market efficiency requires the pure random walk model, excluding constant and trend components, where the mean is constant, and stock price changes are entirely random and influenced by random shocks [12].

Some studies have evaluated different states of capital market efficiency. Rönkkö et al. [13] found that small market size alone does not make a market less efficient; opening a market to foreign investors improves its efficiency after a delay; and the correlation between market volatility and return varies over time in the Finnish stock market, usually being negative. Campisi et al. [14] showed that machine learning models perform better than classic linear regression models in predicting the returns of the American stock market. Gil-Alana et al. [15] found that all individual time series are highly stable, with most cases having an order of integration close to one. Zebende et al. [16] stated that in the short term (less than 5 days), stock markets tend to be efficient, while in the long term (greater than 10 days), they tend to be inefficient. Diallo et al. [17] concluded that the dynamics of indicators reveal characteristics of short-term memory or, in some cases, long-term memory, leading to the rejection of the efficient market hypothesis. Nartea et al. [7] found that stock prices are stationary at higher quantiles, with evidence of asymmetry in dynamic stock price adjustments at these quantiles; larger shocks are associated with faster mean reversion, while smaller shocks are linked to increased volatility. Jansen [18] discovered that market efficiency is not time-invariant and that stock markets have become more efficient over the sample period. Durusu-Ciftci et al. [19] provided strong evidence for the weak efficiency of stock markets.

According to the literature review, the hypothesis of this research is expressed as follows:

The stock prices of large Iranian companies exhibit weak efficiency.

3. Methodology

Koenker and Xiao [20] introduced unit root quantile autoregression which is a type of an augmented dickey-fuller test (ADF). The simulation results show that the unit root quantile autoregression test works better than the standard ADF test when a shock has heavy tail behavior. This test provides a variety of correction mechanisms for long-term equilibrium in different quantities which can be considered an advantage over the ADF test. The Standard ADF test which is used for the unit root quantile autoregression is as follows:

$$p_t = \beta_1 p_{t-1} + \varepsilon_t \quad (1)$$

here, p_t is the index price at time *t*. In Equation (1), the autoregressive coefficient β_1 plays an important role in measuring the stability of economic and financial series. If this coefficient value is 1, the stock price has a unit root or follows a random walk process. In this case, it is not possible to predict future stock prices based on past events because the effect of any kind of shock on prices will be permanent which means that the market is efficient. Conversely, if β_1 is less than one, the stock price is a stationary process and follows the mean-reversion process. The effect of shocks on stochastic (unit root) time series is continually temporary and these effects disappear over time and the series returns to its long-term mean. So, it is possible to predict the stock price based on its past behavior. Koenker and Xiao [20] denote the *τ*-th conditional quantile of p_t as follows:

$$Q_{p_t}(\tau|\mathrm{p}_{t-1}) = \beta_\varepsilon(\tau) + \beta_1(\tau)p_{t-1} \tag{2}$$

where $Q_{p_t}(\tau|p_{t-1})$ is *τ*-th conditional quantile on the past information and $\beta_\varepsilon(\tau)$ is *τ*-th conditional quantile of ε_t where $\{\varepsilon_t\}$ is a random variable i.i.d with mean zero and σ^2 variance. The coefficients of the linear quantile autoregressive model are estimated by minimizing the sum of asymmetric weight deviations.

$$\min_{\beta \in R^2} \sum_{t=1}^{n} \rho_\tau(p_t - x_t\beta) \tag{3}$$

Koenker and Bassett [21] introduced this formula as a check function:

$$\rho_\tau(\varepsilon) = \varepsilon(\tau - I(\varepsilon < 0))$$

In Equation (3), $\beta(\tau) = (\beta_0(\tau), \beta_1(\tau))$ and $x_t = (1, p_{t-1})$. By estimating Equation (3), It is possible to test the random properties of p_t of *τ*-th quantile of using the following *t*-statistic:

$$t_n^*(\tau_\mathrm{i}) = \frac{\hat{f}\left(F^{-1}(\tau_i)\right)}{\sqrt{\tau_i(1-\tau_i)}}(P'_{-1}E_x P_{-1})^{1/2}\left(\widehat{\beta_1}(\tau_i) - 1\right) \tag{4}$$

P_{-1} in Equation (4) is the dependent variable vector with p_{t-1} '(E_x) lag on projection matrix on the orthogonal space *x* and $\hat{f}\left(\mathrm{F}^{-1}(\tau_i)\right)$ is the consistent estimator as follows [20]:

$$\hat{f}\left(F^{-1}(\tau_i)\right) = \frac{(\tau_i - \tau_{i-1})}{x'\left(\beta(\tau_i) - \beta(\tau_{i-1})\right)} \tag{5}$$

Using $t_n^*(\tau_i)$ statistics, the unit root hypothesis can be tested in any quantile. It is noteworthy that $t_n^*(\tau_i)$ is the abnormal distributions and unite root hypothesis cannot be tested using conventional distributions. Therefore, Koenker and Xiao [20] measured the critical values of the quantiles using the "Resampling Method" and "Bootstrap procedure".

Introduced by Ito et al. [22,23] and Noda [24], the degree of efficiency of quantiles is introduced as follows:

$$\hat{\delta}(\tau) = \left|\frac{1-\hat{\beta}_1(\tau)}{\hat{\beta}_1(\tau)}\right| \tag{6}$$

Since the estimated coefficient $\hat{\beta}_1$ is different in each quantile, the degree of efficiency ($\hat{\delta}(\tau)$) in each quantile change. If the autoregressive coefficient $\hat{\beta}_1$ is equal to 1 in the *τ*-th quantile, $\hat{\delta}(\tau)$ is zero, which means that the stock price is efficient in the *τ*-th quantile. As mentioned above, when the stock price follows a random walk process, $\hat{\beta}_1 = 1$, it is not possible to predict the stock price according to the previous information and this suggests the stock efficiency ($\hat{\delta} = 0$). However, if the stock price follows the mean reversion process ($\hat{\beta}_1 < 1$), the stock price can be predicted based on past data, and this indicates the inefficiency ($\hat{\delta} > 0$). The higher the degree of efficiency deviation from zero, the lower the efficiency is. In Quantile Autoregression, the autoregression coefficients may be different in different quantiles. In this case, the degree of efficiency can be measured for different quantiles. That is, the efficiency of the stock price is different in the range of different prices. In other words, the efficiency of the stock price is dynamic.

4. Data

The daily stock price data of 30 large companies on the Tehran Stock Exchange (TSE) have been used in this paper. The data was collected when these companies were listed to the stock market until 1 February 2022. The data are collected from the TSE website (www.tse.ir).

Table 1 shows the descriptive summarized statistics about the stock prices of 30 large companies listed on the TSE. These companies have 30 percent of the TSE value. Here are some crucial points: As shown in **Table 1**, the period under consideration for each stock is different because the period was chosen based on the availability of data. Since the increase in capital causes a price adjustment, the price has been adjusted. That is why the prices of some stocks in **Table 1** are very high, such as the stock of KEGOL Company which is 6,064,156 IRR at maximum. The highest number of observations is related to Qadir Holding Company, which covers 2996 days, and the lowest number is related to Social Security Investment Company (SHASTA), which covers 337 days.

Table 1. Daily price returns descriptive statistics, %.

Name	Index	Period	Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Obs
Telecommunication company of Iran	AKHABER	2009/3/16 2022/2/1	0.15	−0.05	51.1	−11.5	2.1	664	144.3	2807
Khozestan steel company	FAKHOZ	2008/12/6 2022/2/1	0.2	−0.02	31.3	−30.3	2.3	30.3	389.4	2694
Copper company of Iran	FAMELI	2008/12/6 2022/2/1	0.2	−0.03	20.0	−12.5	2.1	688.4	987.6	2948
Persian Gulf petrochemical industries	FARS	2013/3/18 2022/2/1	0.2	−0.1	11.4	−13.9	1.9	11.7	704.4	1992
Isfahan steel company	FILAD	2008/12/6 2022/2/1	0.19	−0.05	16.0	−16.1	2.1	28.5	755.6	2933
Golgohar industrial and mining company	KEGOL	2008/12/6 2022/2/1	0.2	−0.04	21.1	−13.5	2.0	89.1	1067.2	2827
Mobile communications company of Iran	HAMRAH	2013/8/20 2022/2/1	0.16	−0.02	9.2	−5.1	1.6	44.9	683.7	1985
Chadormalo industrial and mining company	KACHAD	2008/12/6 2022/2/1	0.19	−0.06	23.0	−24.2	2.1	73.2	1827.6	2894
Shipping of the Islamic Republic of Iran	HAKESHTI	2008/12/6 2022/2/1	0.12	−0.02	115.9	−20.8	3.1	1984	7313.3	2769
Saipa car company	KHASAPA	2008/12/6 2022/2/1	0.17	0.00	71.0	−25.8	3.2	505.2	1113.4	2824
Irankhodro car company	KHODRO	2008/12/6 2022/2/1	0.17	0.00	69.3	−12.2	3.1	515.8	1085	2750
Mapna Group	MAPNA	2008/12/6 2022/2/1	0.21	0.00	21.2	−15.4	2.5	33.8	778.1	2642
Mellat Bank	VEBMELAT	2009/2/1 2022/2/1	0.15	0.00	38.1	−47.0	2.4	189.2	8729	2690
Nori petrochemical	NORI	2019/7/13 2022/2/1	0.45	0.13	13.4	−5.1	3.1	17.4	270.5	590
Omid investment management group	OMID	2008/12/6 2022/2/1	0.2	−0.02	11.2	−9.1	1.6	59.7	640.7	2865

Table 1. (*Continued*).

Name	Index	Period	Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Kurtosis	Obs
Parsian oil and gas development	PARSAN	2012/2/15 2022/2/1	0.19	−0.04	17.1	−11.8	2.2	32.03	598.4	2234
Parsian Bank	PARSIAN	2008/12/6 2022/2/1	0.17	−0.07	28.3	−10.8	2.3	116.7	1496.9	2517
Pars petrochemical	PARS	2018/7/11 2022/2/1	0.31	0.04	9.6	−5.1	2.5	7.8	280.9	838
Qadir holding	VEQADIR	2009/2/1 2022/2/1	0.19	−0.06	23.4	−6.1	2.1	88.1	1020	2996
Pardis Petrochemical	SHAPDIS	2011/11/26 2022/2/1	0.2	−0.04	9.6	−5.2	1.9	32.4	447.8	2252
Isfahan oil company	SHAPNA	2008/12/6 2022/2/1	0.22	−0.02	22.3	−14.01	2.5	65.7	866.0	2411
Social security investment company	SHASTA	2020/4/15 2022/2/1	0.66	0.6	26.5	−19.7	4.4	56.7	1077	337
Bandar abbas oil company	SHEBANDAR	2012/6/24 2022/2/1	0.27	0.01	19.5	−19.3	2.8	12.1	701.6	1817
Tehran oil company	SHETRAN	2016/10/30 2022/2/1	0.28	0.00	23.9	−12.3	2.9	71.3	793.7	1182
Tamin Petrochemical, oil and gas company	TAPIKO	2013/7/9 2022/2/1	0.14	−0.01	16.3	−10.1	2.2	35.5	576.4	1890
Mining and metals development company	VEMADEN	2008/12/6 2022/2/1	0.19	−0.05	11.7	−20.0	2.3	7.4	672.2	2779
Pasargad Bank	VAPASAR	2011/8/16 2022/2/1	0.17	−0.03	28.5	−8.2	2.1	169.5	2251	1884
Pension fund investment company	VASANDOQ	2008/12/6 2022/2/1	0.18	−0.04	28.3	−10.3	2.0	156.6	2111.3	2885
Tejarat Bank	VATEJARAT	2009/6/13 2022/2/1	0.18	0.00	25.7	−41.2	2.3	139.9	511.2	2613
Saderat Bank	VEBASADER	2009/6/9 2022/2/1	0.15	0.00	14.0	−67.8	2.6	801.1	219.1	2463

Source: www.tse.ir.

Descriptive statistics

The average return of these 30 companies is positive, ranging from 0.12 percent (HAKESHTI stock symbol) to 0.45 percent (NORI stock symbol) daily. The negative median for some companies suggests that the number of days with negative returns exceeds the number of days with positive returns. Among these 30 companies, Nouri, Pars, Shasta, and Shebandar companies have positive medians, indicating that the number of days with positive returns is greater than the number of days with negative returns, though they also experienced higher volatility. Shasta company, in particular, is the most volatile, with a standard deviation of 4.4. Additionally, all return series exhibit positive skewness, which indicates that large positive returns are more frequent than large negative returns. In other words, the positive skewness implies that the market experiences more fluctuations and that the stock prices of these 30 companies react more strongly to positive news than to negative news. All kurtosis values are very high, clearly indicating a "skewed distribution".

5. Empirical results

5.1. Random walk hypothesis and structural break tests

Dickey and Fuller [25,26] proposed a reliable process for testing the unite root. It is important to note that the critical values of the t-statistic depend on the presence or absence of a fixed component or trend, as well as the sample size and the optimal lags. The premise of ADF tests is that the error statements are independent of each other and have a constant variance. However, care must be taken when running the unite root test, as the actual process of data generation is unknown. To this end, the approach of Dolado et al. [27] and Hamilton [28] was used to test the unite root. Furthermore, conventional unit root tests are biased toward a false unit root null when the data are trend-stationary but contain a structural break. In short, the presence of structural changes induces a bias in favor of a unit root representation that empirically researchers ought to take into account which has been proven by Monte Carlo studies. Since the time of occurrence of structural break is not known in the stock price data mentioned in **Table 1**, endogenous Perron [29] and Vogelsang and Perron [30] tests have been used the results show that all 30 large companies on the TSE follow a random walk process. Among these, 21 companies follow a pure random walk (without intercept and trend) and 9 companies follow a random walk with an intercept (**Table 2**).

Table 2. Random walk hypothesis and structural break tests.

Company	***K***	**Unit root; No break**			**Unit root; with the endogenous break**				**Inference Random walk**
		Random walk			$y_t = \mu + \alpha y_{t-1} + \theta DU_t(T_B) + \omega D_t(T_B) + \sum_{i=1}^{k} c_i \Delta y_{t-i} + U_t$				
		Pure	**Constant**	**Constant & trend**	T_B	$\hat{\theta}$	$\hat{\omega}$	**ADF statistic**	
AKHABER	3	−2.3	−0.3	−1.6	2019/2/4	0.006*	−0.005	−2.9	Pure
FAKHOZ	3	−3.3	−0.4	−1.5	2017/6/24	0.004*	−0.01	−2.4	With constant
FAMELI	5	−2.9	0.03	−1.1	2018/7/15	0.005*	−0.01	−2.5	Pure
FARS	2	−2.6	0.7	−0.6	2019/3/6	0.007*	−0.007	−2.7	With constant
FILAD	3	−3.6	0.4	−0.9	2017/6/17	0.004*	−0.001	−2.3	With constant
KEGOL	3	−3.5	0.4	−1.1	2017/7/8	0.004*	−0.007	−1.9	Pure
HAMRAH	5	−2.4	−0.5	−2.04	2019/3/17	0.004*	−0.004	−2.4	With constant
KACHAD	2	−3.4	0.8	−0.7	2018/5/21	0.005*	−0.001	−2.1	Pure
HAKESHTI	2	−1.5	−0.2	−1.8	2013/8/26	0.006*	0.006	−2.4	Pure
KHASAPA	3	−1.9	0.1	−1.7	2019/12/29	0.009*	−0.01	−2.2	Pure
KHODRO	3	−2.1	0.2	−1.2	2019/3/12	0.009*	−0.01	−2.8	Pure
MAPNA	3	−2.8	−0.6	−1.8	2018/7/30	0.006*	−0.02	−3.03	Pure
VEBMELAT	2	−2.5	0.5	−0.98	2018/8/7	0.009*	−0.004	−3.4	Pure
NORI	2	−2.2	−1.3	−0.95	2020/5/12	0.02*	−0.06**	−3.6	Pure
OMID	3	−3.9	1.5	−0.8	2018/6/12	0.003*	−0.02	−1.3	With constant
PARSAN	5	−2.6	−0.2	−1.3	2018/6/12	0.01*	−0.01	−3.6	Pure
PARSIAN	3	−2.2	0.1	−0.99	2020/1/11	0.006*	−0.006	−2.6	Pure
PARS	2	−2.3	−1.3	−1.9	2020/3/25	0.01*	0.02	−2.8	Pure
VEQADIR	3	−3.3	−0.9	−1.8	2018/6/11	0.004*	−0.004	−2.9	With constant
SHAPDIS	3	−3.7	0.3	0.7	2018/6/12	0.006*	−0.005	−1.9	With constant
SHAPNA	1	−2.2	0.3	−2.04	2018/6/12	0.007*	−0.006	−2.7	Pure
SHASTA	1	−1.1	−2.6	−1.7	2020/5/26	0.01*	−0.06	−2.6	Pure
SHEBANDAR	1	−2.4	−1.6	−1.9	2018/7/17	0.01*	−0.009	−2.2	With constant
SHETRAN	3	−1.7	−0.9	−2.6	2018/7/17	0.007*	−0.002	−2.9	Pure
TAPIKO	3	−1.7	0.04	−1.1	2019/7/16	0.009*	−0.05**	−2.9	Pure
VEMADEN	5	−2.9	0.09	−1.4	2018/5/23	0.005*	−0.003	−2.3	Pure
VAPASAR	3	−2.3	1.5	0.65	2020/1/8	0.01*	−0.02	−3.1	Pure
VASANDOQ	1	−2.4	0.5	−1.5	2018/6/12	0.003*	−0.002	−1.7	With constant
VATEJARAT	1	−2.9	0.7	−0.7	2018/8/6	0.007*	−0.04	−2.9	Pure
VEBASADER	1	−2.2	0.001	−1.5	2020/1/8	0.009*	−0.02	−2.6	Pure

The inference is based on tests for the presence of deterministic components ($\emptyset_i$) Dickey and Fuller [26] and structural break test; break time is endogenously calculated from the data; critical values of ADF with break are −4.95, −4.44, −4.19 respectively at levels of %1, %5 and %10; * and ** indicate the significance of level at %1and %5 respectively.

According to Fama [2], the prices of those companies that follow the pure random walk process have weak efficiency. In fact, the stock price of these companies the next day will be the same as the previous day, in addition to the shocks that will occur on the current day. But the data generation process in companies whose price follows a random walk with intecept, there is a constant component, which is the additional return that accrues to the buyer of stocks.

Therefore, according to the results of these two tests, Akhaber, Femeli, Kegol, Kachad, Hakeshti, Khasapa, Khodro, Mapna, Vebmelat, Nouri, Parsan, Parsian, Pars, Shapna, Shasta, Shetran, Tapiko, Vemaden, Vepasar, and Vetejarat and Vebsader companies have weak efficiency. On the other hand, Fakhuz, Fars, Foulad, Hamrah, Omid, Veqadir, Shapdis, Shebandar, and Vasaondoq companies did not have weak efficiency.

5.2. Quantile random walk hypothesis test

In **Table 2**, we performed a unit root test on the price logarithms of 30 companies on the TSE. Results based on ADF statistics show that 9 companies have a random walk process with an interception and 21 companies followed price based on a random walk without intercept and trend components which are known as the pure random walk process. For a time series process, if this process is a random walk with no intercept and no trend when testing the unit root, then the process is completely random (pure random). If a process is a random walk with intercept or trend components the process has predictable by these components. Therefore, the process is not completely random, because the intercept component and trend are predictable.

On the other hand, according to efficient markets theory, the price must be a completely random walk to investors cannot use information from past prices to predict future prices. This concept is consistent with the above-mentioned purely random walks. Therefore, a company's stock exchange is efficient with a purely random process. In **Table 2**, the stock prices of 21 companies have a pure random walk process, so the stock prices of these companies are traded in the efficient market. The stock price trend of the other 9 companies including FAKHOZ, FARS, FOLAD, HAMRAH, OMID, VEQADIR, SHAPDIS, SHEBANDAR, and VASANDOQ consists of a random walk with the intercept, which is a predictable component of the intercept. So, it cannot be claimed that the stock prices of these companies are trading in an efficient market. Another question is whether the market is efficient at all levels of stock prices. The quantile unit root test was used for this purpose. **Table 3** shows the results of the quantile unit root estimates of the stock price of 30 companies of 9 deciles. As the autoregressive coefficient is close to one, the efficient market claim is strengthened. In most cases, it is observed that the autoregressive coefficient is close to or equal to 1. However, there are subtle differences between deciles. For almost all stocks, the autoregressive coefficient is very close to 1 for middle deciles such as 5 and 6, and far from 1 for upper and lower deciles. That is, performing a regression on the lower or upper decile reduces the efficient stock price hypothesis, and performing a regression on the middle decile strengthens the efficient market hypothesis.

Equation (6) was defined to better identify various decile performance situations. If the autoregressive coefficient is equal to 1, the index value of $\hat{\delta}(\tau)$ will be zero. This means that the market is efficient.

Table 3. Quantile random walk hypothesis test.

Company	**Quantiles**	**0/1**	**0/2**	**0/3**	**0/4**	**0/5**	**0/6**	**0/7**	**0/8**	**0/9**
AKHABER	$\hat{\beta}_1(\tau)$	0.998(−15.1)	0.999(−16.3)	0.999(−16.2)	0.999(−11.9)	0.999(−3.4)	1.000(3.9)	1.000(10.1)	1.001(13.6)	1.002(17.1)
	$t_n^*(\tau_i)$	−18.6***	−18.01***	−17.1***	−12.9***	−5.2***	5.1***	11.5***	14.3***	23.8***
FAKHOZ	$\hat{\beta}_0(\tau)$	0.05(13.2)	0.03(13.7)	0.02(7.4)	0.01(4.03)	0.002(0.99)	−0.01(−2.6)	−0.02(−6.3)	−0.03(−8.7)	−0.02(−2.7)
	$\hat{\beta}_1(\tau)$	0.994(−15.5)	0.997(−15.5)	0.998(−8.4)	0.999(−4.7)	0.999(−1.2)	1.001(3.01)	1.002(7.8)	1.004(11.3)	1.005(5.4)
	$t_n^*(\tau_i)$	−14.3***	−16.8***	−14.6***	−12.2***	−4.02***	6.4***	9.01***	8.9***	5.8***
FAMELI	$\hat{\beta}_1(\tau)$	0.998(−21.3)	0.999(−22.7)	0.999(−18.5)	1.000(−12.1)	1.000(−2.1)	1.000(7.7)	1.001(12.9)	1.001(19.1)	1.002(33.5)
	$t_n^*(\tau_i)$	−24.2***	−25.01***	−17.7***	−13.6***	−2.8**	8.1***	13.1***	21.1***	37.1***
FARS	$\hat{\beta}_0(\tau)$	0.1(11.8)	0.08(7.8)	0.04(3.9)	0.02(2.8)	0.0005(0.09)	−0.03(−2.7)	−0.07(−10.8)	−0.08(−7.9)	−0.08(−6.2)
	$\hat{\beta}_1(\tau)$	0.988(−13.3)	0.991(−8.3	0.995(−4.1)	0.998(−3.00)	0.999(−0.2)	1.003(2.8)	1.008(11.1)	1.009(8.9)	1.009(8.1)
	$t_n^*(\tau_i)$	−17.4***	−23.5***	−18.8***	−15.03***	−0.75	22.6***	21.6***	15.8***	8.3***
FILAD	$\hat{\beta}_0(\tau)$	0.1(2.4)	0.009(2.6)	0.01(5.3)	0.006(1.9)	0.0009(0.35)	−0.003(−0.9)	−0.006(−1.6)	−0.01(−2.9)	0.0009(0.2)
	$\hat{\beta}_1(\tau)$	0.997(−5.9)	0.998(−5.4)	0.998(−7.4)	0.999(−2.7)	0.999(−0.4)	1.000(1.8)	1.001(3.5)	1.003(6.7)	1.003(5.7)
	$t_n^*(\tau_i)$	−6.1***	−6.4***	−9.6***	−6.1***	−0.8	2.4*	4.2***	6.3***	5.4***
KEGOL	$\hat{\beta}_1(\tau)$	0.998(−16.7)	0.999(−17.7)	0.999(−17.4)	0.999(−10.9)	0.999(−1.7)	1.000(5.7)	1.000(11.4)	1.001(17.6)	1.002(25.9)
	$t_n^*(\tau_i)$	−17.2***	−19.2***	−19.1***	−11.8***	−3.3***	6.3***	13.1***	20.3***	31.8***
HAMRAH	$\hat{\beta}_0(\tau)$	0.1(15.3)	0.06(9.7)	0.03(6.1)	0.01(3.4)	0.0003(0.1)	−0.01(−3.33)	−0.03(−7.2)	−0.06(−13.7)	−0. 1(−13.2)
	$\hat{\beta}_1(\tau)$	0.99 (−16.0)	0.994(−10.1)	0.997(−6.5)	0.999(−3.6)	0.999(−0.1)	1.001(3.5)	1.003(7.5)	1.006(14.4)	1.009(14.1)
	$t_n^*(\tau_i)$	−27.5***	−23.1***	−19.8***	−11.5***	−0.5	10.04*	14.2***	15.7***	15.2***
KACHAD	$\hat{\beta}_1(\tau)$	0.998(−19.4)	0.999(−17.0)	0.999(−18.7)	0.999(−12.1)	0.999(−2.9)	1.000(3.9)	1.000(10.2)	1.001(17.5)	1.002(22.8)
	$t_n^*(\tau_i)$	−18.4***	−18. 9***	−19.4***	−15.3***	−4.8**	5.0***	10.8***	17.5***	40.2***
HAKESHTI	$\hat{\beta}_1(\tau)$	0.998(−15.6)	0.999(−13.7)	0.999(−12.2)	0.999(−10.8)	0.999(−3.4)	1.000(1.9)	1.000(6.6)	1.001(6.3)	1.002(16.9)
	$t_n^*(\tau_i)$	−16.6***	−15. 9***	−15.3***	−12.3***	−4.7**	3.2***	8.7***	11.3***	27.5***
KHASAPA	$\hat{\beta}_1(\tau)$	0.996(−47.5)	0.997(−25.3)	0.998(−15.4)	0.999(−7.3)	1.000(0.04)	1.000(8.9)	1.001(18.9)	1.002(26.7)	1.004(51.9)
	$t_n^*(\tau_i)$	−62.1***	−26. 5***	−17.4***	−7.6***	0.1	7.9***	20.7***	38.3***	96.8***
KHODRO	$\hat{\beta}_1(\tau)$	0.996(−43.8)	0.997(−18.1)	0.998(−14.8)	0.999(−8.5)	1.000(0.4)	1.000(9.1)	1.001(15.8)	1.002(28.9)	1.004(56.2)
	$t_n^*(\tau_i)$	−43.7***	−17. 4***	−14.6***	−8.9***	1.1	6.5***	14.8***	31.2***	70.7***
MAPNA	$\hat{\beta}_1(\tau)$	0.997(−31.0)	0.998(−20.3)	0.999(−15.6)	0.999(−8.8)	1.000(0.01)	1.000(8.4)	1.001(15.9)	1.002(21.4)	1.004(38.2)
	$t_n^*(\tau_i)$	−28.7***	−21. 6***	−15.9***	−9.9***	0.01	8.2***	15.5***	26.1***	68.1***

Table 3. (*Continued*).

Company	Quantiles	0/1	0/2	0/3	0/4	0/5	0/6	0/7	0/8	0/9
VEBMELAT	$\hat{\beta}_1(\tau)$	0.997(−26.3)	0.998(−17.4)	0.999(−13.9)	0.999(−7.7)	1.000(0.00)	1.000(7.2)	1.001(11.6)	1.002(18.5)	1.003(31.2)
	$t_n^*(\tau_i)$	−24.2***	−18. 4***	−14.9***	−8.2***	0.00	7.1***	12.2***	22.0***	38.7***
NORI	$\hat{\beta}_1(\tau)$	0.997(−14.9)	0.998(−11.1)	0.999(−7.5)	0.999(−3.5)	1.000(0.2)	1.000(4.8)	1.001(8.4)	1.002(10.7)	1.003(20.7)
	$t_n^*(\tau_i)$	−16.2***	−12. 3***	−8.5***	−4.2***	0.2	5.5***	10.6***	13.9***	43.4***
OMID	$\hat{\beta}_0(\tau)$	0.02(5.6)	0.01(6.2)	0.004(3.1)	0.001(1.3)	−0.001(−0.6)	−0.003(−2.3)	−0.009(−4.7)	−0.02(−6.1)	−0.02(−4.7)
	$\hat{\beta}_1(\tau)$	0.997(−8.8)	0.998(−7.6)	0.999(−4.4)	0.999(−2.1)	1.000(0.4)	1.000(2.6)	1.001(5.3)	1.002(7.7)	1.004(8.4)
	$t_n^*(\tau_i)$	−7.7***	−10.1***	−6.3***	−3.7***	1.8	6.7*	8.7***	8.7***	6.5***
PARSAN	$\hat{\beta}_1(\tau)$	0.998(−19.7)	0.999(−17.5)	0.999(−15.1)	0.999(−8.4)	0.999(−1.0)	1.000(7.3)	1.001(13.8)	1.002(21.6)	1.003(25.3)
	$t_n^*(\tau_i)$	−21.8***	−18. 2***	−13.9***	−10.9***	−1.2	7.7***	15.4***	22.2***	35.5***
PARSIAN	$\hat{\beta}_1(\tau)$	0.997(−21.9)	0.999(−18.9)	0.999(−13.4)	0.999(−8.4)	0.999(−0.7)	1.000(6.2)	1.001(11.1)	1.001(18.6)	1.003(18.7)
	$t_n^*(\tau_i)$	−22.0***	−20. 4***	−14.8***	−9.5***	−1.3	7.0***	12.4***	21.7***	36.8***
PARS	$\hat{\beta}_1(\tau)$	0.998(−16.7)	0.999(−12.2)	0.999(−7.9)	0.999(−3.1)	1.000(0.2)	1.000(5.1)	1.001(9.5)	1.002(12.9)	1.003(18.4)
	$t_n^*(\tau_i)$	−19.2***	−10. 5***	−8.4***	−3.8***	0.3	4.9***	9.5***	12.5***	29.2***
VEQADIR	$\hat{\beta}_0(\tau)$	0.01(1.5)	0.01(3.9)	0.01(2.5)	0.004(1.5)	0.004(1.2)	0.004(1.2)	0.002(0.4)	−0.001(−0.3)	0.003(0.8)
	$\hat{\beta}_1(\tau)$	0.997(−5.0)	0.998(−7.0)	0.999(−4.2)	0.999(−2.4)	0.999(−1.3)	0.999(−0.6)	1.000(0.8)	1.002(3.8)	1.003(6.8)
	$t_n^*(\tau_i)$	−4.9***	−6.4***	−5.2***	−4.1***	−3.1**	−0.9	1.1	3.2**	4.9***
SHAPDIS	$\hat{\beta}_0(\tau)$	0.08(8.5)	0.04(5.9)	0.03(5.2)	0.02(2.9)	0.002(0.4)	−0.02(−2.2)	−0.04(−5.9)	−0.06(−9.1)	−0.06(−7.4)
	$\hat{\beta}_1(\tau)$	0.992(−9.9)	0.996(−6.8)	0.997(−5.7)	0.998(−3.3)	0.999(−0.5)	1.002(2.3)	1.004(6.4)	1.006(10.7)	1.007(10.7)
	$t_n^*(\tau_i)$	−11.3***	−10.4***	−13.0***	−11.2***	−2.0	6.9*	8.9***	10.2***	7.5***
SHAPNA	$\hat{\beta}_1(\tau)$	0.997(−26.5)	0.999(−18.5)	0.999(−14.8)	0.999(−8.5)	0.999(−0.6)	1.000(6.3)	1.001(13.4)	1.002(18.4)	1.003(42.2)
	$t_n^*(\tau_i)$	−29.1***	−17. 4***	−16.2***	−10.2***	−1.6	6.7***	14.0***	19.2***	67.3***
SHASTA	$\hat{\beta}_1(\tau)$	0.996(−12.4)	0.997(−7.6)	0.998(−4.3)	0.999(−2.0)	1.000(0.5)	1.001(2.8)	1.002(3.3)	1.004(7.3)	1.005(13.8)
	$t_n^*(\tau_i)$	−17.9***	−8.5***	−4.8***	−2.7**	0.4	3.9***	9.7***	37.7***	44.6***
SHEBANDAR	$\hat{\beta}_0(\tau)$	0.01(0.9)	0.04(4.0)	0.03(3.0)	0.03(2.9)	0.01(1.0)	0.01(0.7)	0.004(0.4)	0.005(0.9)	0.02(3.8)
	$\hat{\beta}_1(\tau)$	0.996(−4.7)	0.994(−6.1)	0.996(−4.0)	0.997(−3.2)	0.999(−0.9)	0.999(−0.02)	1.001(1.2)	1.002(3.4)	1.002(5.6)
	$t_n^*(\tau_i)$	−4.8***	−6.6***	−5.7***	−6.1***	−2.0	−0.03	1.4	2.4	4.5***
SHETRAN	$\hat{\beta}_1(\tau)$	0.997(−19.4)	0.998(−17.1)	0.999(−11.3)	0.999(−6.5)	0.999(−0.5)	1.000(5.5)	1.001(11.0)	1.002(14.6)	1.003(20.3)
	$t_n^*(\tau_i)$	−26.6***	−17.0***	−14.6***	−7.5***	−0.6	6.9***	12.8***	20.2***	28.6***
TAPIKO	$\hat{\beta}_1(\tau)$	0.997(−18.6)	0.998(−18.3)	0.999(−15.0)	0.999(−9.2)	0.999(−2.3)	1.000(5.2)	1.001(10.8)	1.002(13.7)	1.003(26.5)
	$t_n^*(\tau_i)$	−20.4***	−20.4***	−16.0***	−11.8***	−3.9***	5.6***	11.8***	15.4***	34.1***

Table 3. (*Continued*).

Company	Quantiles	0/1	0/2	0/3	0/4	0/5	0/6	0/7	0/8	0/9
VEMADEN	$\hat{\beta}_1(\tau)$	0.998(−20.0)	0.999(−21.5)	0.999(−16.9)	0.999(−10.3)	0.999(−1.1)	1.000(6.6)	1.001(12.2)	1.002(19.8)	1.003(36.0)
	$t_n^*(\tau_i)$	−22.4***	−21.7***	−18.6***	−11.5***	−2.03	7.5***	12.8***	24.3***	46.3***
VAPASAR	$\hat{\beta}_1(\tau)$	0.997(−17.8)	0.999(−16.0)	0.999(−12.9)	0.999(−8.2)	0.999(−1.5)	1.000(4.2)	1.001(8.9)	1.002(14.1)	1.003(21.9)
	$t_n^*(\tau_i)$	−18.3***	−17.7***	−13.1***	−10.4***	−2.3*	5.3***	8.9***	13.8***	24.8***
VASANDOQ	$\hat{\beta}_0(\tau)$	0.03(5.0)	0.02(6.4)	0.01(6.5)	0.005(4.7)	0.001(1.0)	−0.003(−2.3)	−0.01(−6.0)	−0.03(−9.1)	−0.02(−3.0)
	$\hat{\beta}_1(\tau)$	0.995(−7.9)	0.997(−7.7)	0.999(−7.8)	0.999(−5.6)	0.999(−1.2)	1.000(2.6)	1.002(6.4)	1.004(10.9)	1.004(8.2)
	$t_n^*(\tau_i)$	−8.0***	−10.6***	−9.5***	−13.5***	−7.1***	7.7***	12.5***	9.9***	6.6***
VATEJARAT	$\hat{\beta}_1(\tau)$	0.998(−21.3)	0.999(−15.9)	0.999(−11.2)	0.999(−6.4)	1.000(0.00)	1.000(5.5)	1.001(9.3)	1.002(13.4)	1.003(17.3)
	$t_n^*(\tau_i)$	−19.8***	−19.4***	−11.7***	−7.2***	0.00	6.7***	9.9***	13.3***	37.7***
VEBASADER	$\hat{\beta}_1(\tau)$	0.997(−20.7)	0.999(−16.3)	0.999(−11.4)	0.999(−5.6)	1.000(0.00)	1.000(5.4)	1.001(9.0)	1.002(17.4)	1.003(26.1)
	$t_n^*(\tau_i)$	−22.6***	−17.4***	−11.4***	−8.8***	0.00	5.9***	9.2***	16.0***	41.9***
$t_n^*(\tau_i)$ Critical Values	%1	−2.78	−2.91	−3.06	−3.14	−3.19	−3.24	−3.3	−3.36	−3.39
	%5	−2.12	−2.28	−2.4	−2.51	−2.58	−2.64	−2.72	−2.75	−2.81
	%10	−1.75	−1.92	−2.06	−2.17	−2.25	−2.32	−2.41	−2.46	−2.5

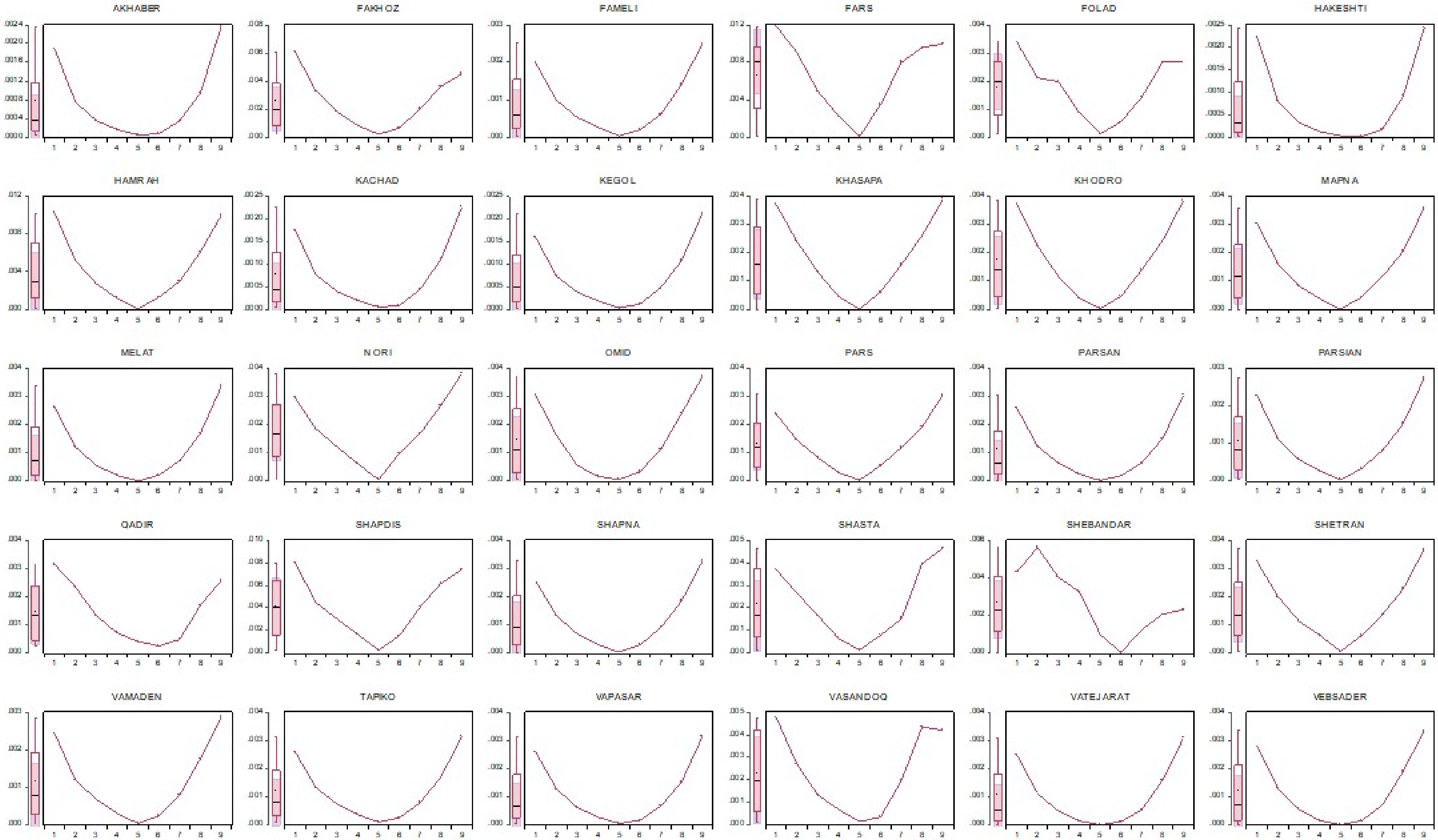

Figure 1. Efficiency degree [$\hat{\delta}(\tau)$ in Equation (6)] of 30 large companies of TSE in 9 deciles.

According to Equation (6) as the autoregressive coefficient moves away from one, the value of $\hat{\delta}(\tau)$ also moves away from zero (**Figure 1**). This means that the market will be less efficient. The results show that running the autoregressive model in the lower or upper decile reduces market efficiency for all companies (**Figure 1**). However, running the autoregressive model in the middle decile increases the market efficiency. When the regression basis of the first decile is considered, according to the result, the market efficiency is lower than that of the middle regression basis. Likewise, if the regression basis of the upper decile is considered, for example, the ninth decile, the market efficiency will be less than the case where the regression basis is average or median.

The practical implication of the above is that market efficiency drops at very high and very low prices. At average and median prices, the market is more efficient. When prices are very low, investors can often predict that stocks will return to average prices to some extent. Investors can, to some extent, predict that stock prices will return to average, even if prices are high. However, if the stock price is on a long-term average, it is difficult to predict that trend, and the best prediction is the current price (That is, a random walk process). The market efficiency trend for most stocks of companies such as AKHABER, KACHAD, and KEGOL increases slowly and with a gentle trend, moving from the first to the fifth decile (**Figure 1**). However, for some stocks of companies such as FARS, FOLAD, NORI, and SHETRAN, the market efficiency increases with a steady trend. No company can increase efficiency on sharp trends. This trend continues with the inefficient transition from the 5th to the 9th decile. As a result, the market efficiency of most stocks of the companies surveyed in this study has increased slightly with the move toward the mean of price.

As a general result, the stock market moves towards efficiency if there are no positive and negative shocks that keep stock prices off average, or if the effects of positive and negative shocks are neutralized. In the case of a positive shock when the stock price rises sharply and a negative shock when the stock price falls sharply, the market efficiency decreases. Market efficiency is highest in stable positions where prices are close to the long-term average. The random walk hypothesis is the basis of the efficient market hypothesis, which states that the information available in the market is random and unpredictable (either with directed or undirected expectations). Therefore, random stock price changes are required in efficient markets. The efficient market has no memory. In other words, you cannot predict tomorrow's price from yesterday's price. Therefore, the only way to achieve high profits is to buy high-risk stocks, according to the definitions provided in the efficient market. Stock prices are not always going to be the same as their intrinsic value, according to this hypothesis. Sometimes prices may be higher or lower than intrinsic value. Eventually, prices will return to their median or intrinsic value.

6. Conclusion

This study aims to examine the efficiency of the Tehran Stock Exchange using the stock prices of large companies. In this research, instead of using the stock price index of the stock exchange, the stock prices of large companies have been used to examine the market efficiency. For this purpose, 30 large companies on the Tehran

Stock Exchange were selected. The stock prices of these companies were first examined using the unit root test in two cases, one with no structural break and one with an endogenous structural break. As a result, it was found that the stock prices of 21 companies adopted the pure random walk method, had no intercept and were a component of the random walk method.

Therefore, if we disaggregate the market, most stock prices show market efficiency, but the prices of all companies don't. In other words, the stock prices of some companies show the efficiency of the market, while others do not. Therefore, one of the reasons for the inefficiency of the capital markets as a whole is the inefficiency of the stock prices of some large companies.

In this study, we used quantile regression to find that the stock prices of the low, medium, and high-level differ in terms of efficiency. It is less efficient at low and high price levels, but more efficient at medium price levels. In other words, if the stock price deviates (up or down) from the long-term average, the market becomes inefficient, and when the stock price is at the middle level, which is almost the intrinsic value of the stock, the market efficiency is higher.

Since the results of this article show both efficient and inefficient outcomes, they align with the findings of all reviewed articles. Articles that have found weak efficiency include those by Gil-Alana et al. [15], Zebende et al. [16], Durusu-Ciftci et al. [19], Lu et al. [11], Narayan and Narayan [31], and Chaudhuri and Wu [6]. In contrast, articles that have rejected the efficient market hypothesis include those by Diallo et al. [17], Nartea et al. [7], Hamid et al. [32], and Narayan and Smyth [10]. While previous studies have focused on testing the random walk hypothesis for common indices in developed, developing, and emerging countries, it is crucial to test this hypothesis using various types of data, markets, indices, and time periods. Although weak market efficiency has been examined in many global stock markets, results have varied due to differences in study methodologies, data availability, and study periods.

To address these inconsistencies, future research should consider the following suggestions: Expand data sources to include different asset classes and market segments, broaden market coverage to include less frequently studied markets, and extend the periods analyzed to capture a wider range of market conditions. Additionally, refining methodologies and statistical techniques, as well as investigating how different market conditions impact efficiency, can provide a more nuanced and comprehensive understanding of market efficiency.

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