The Impact of Market Efficiency on Stock Fair Value: Evidence from Arab Markets

Mahmoud Abdelaziz Touny [1]   Nour Mahmoud Abdelaziz [2]

Abstract

The purpose of this study is to assess the impact of market efficiency on stock fair value using data from Arab countries, including Egypt, Morocco, Tunisia, Saudi Arabia, the UAE, Kuwait, Oman, and Qatar, from 2004 to 2022. The study employs a dynamic panel data methodology that incorporates both time series and cross-sectional data, as well as a linear regression model based on the fixed effects method. The findings suggest that most indicators of stock market efficiency have a positive and statistically significant effect on the fair value of stocks. However, the volume indicator shows a weak negative effect at a 10% significance level.

Keywords: Market Efficiency, Stock Fair Value, financial markets, dynamic panel data, Fixed Effects (FE) Method, Stock Market Efficiency**.**

[1] **Professor of Economics, Faculty of Commerce and Business Administration, Helwan University, Egypt . Email: prof.mahmoudtouny@yahoo.com**

[2] Master Researcher, Faculty of Commerce and Business Administration, Helwan University, Egypt.

أثر كفاءة السوق على القيمة العادلة للأسهم: أدلة من الأسواق العربية

الملخص

تهدف هذه الدراسة إلى تقييم أثر كفاءة السوق على القيمة العادلة للأسهم باستخدام بيانات من الدول العربية، بما في ذلك مصر والمغرب وتونس والمملكة العربية السعودية والإمارات العربية المتحدة والكويت وعمان وقطر، من عام 2004 إلى عام 2022. وتستخدم الدراسة نموذج ديناميكي لمزيج من بيانات السلاسل الزمنية والمقطعية باستخدام نموذج الانحدار الخطي بطريقة الأثار الثابتة. وتشير النتائج إلى أن معظم مؤشرات كفاءة سوق الأوراق المالية لها تأثير إيجابي وذو دلالة إحصائية على القيمة العادلة للأسهم. ومع ذلك، يظهر مؤشر الحجم تأثير عكسي عند مستوى معنوية إحصائية ضعيفة 10%.

الكلمات المفتاحية: كفاءة السوق، القيمة العادلة للأسهم، الأسواق المالية، نماذج السلاسل الزمنية المقطعية الديناميكية، نموذج التأثيرات الثابتة (FE)، كفاءة سوق الأوراق المالية.

1/ Introduction:

In the complex world of financial markets, understanding the factors that drive stock prices is pivotal for investors, policymakers, and corporations alike. Market efficiency, a cornerstone concept in financial economics, plays a crucial role in determining the fair value of stocks. It reflects how swiftly and accurately information is integrated into stock prices, shaping the dynamics of investment decisions and resource allocation. Despite extensive research, the relationship between market efficiency and fair value remains a topic of debate, with varying impacts observed across different markets and economic conditions.

This research goes into this complex relationship, analyzing how several aspects of market efficiency—such as stock turnover, market capitalization, and trading volume—influence the fair value of stocks, as measured by Tobin's Q. This study attempts to provide a comprehensive understanding of how market efficiency might influence the creation of value in stock markets, utilizing lessons from worldwide financial environments.

2/ Research Problem:

Despite the central role that market efficiency plays in financial theory and practice, the precise impact of market efficiency on the fair value of stocks remains inadequately understood and highly debated. While efficient markets are presumed to reflect all available information in stock prices, leading to fair valuations, empirical evidence presents a more complex and often contradictory picture. Some studies suggest that greater efficiency reduces mispricing and aligns stock prices more closely with their intrinsic values, while others highlight anomalies, such as market bubbles or crashes, even in highly liquid markets.

This inconsistency becomes more pronounced in emerging markets like Egypt, where market efficiency is still evolving and is influenced by varying factors such as trading volume, market turnover, and investor behavior. There is a need for more comprehensive research that investigates how these dimensions of market efficiency affect the fair value of stocks, especially in the context of different economic environments and regulatory frameworks. Understanding this relationship is crucial for investors seeking accurate valuations, for corporations making strategic financial decisions, and for policymakers aiming to foster stable and transparent markets.

3/ Hypothesis Statement:

This paper aims to explore the impact of market efficiency on the fair value of stocks, particularly focusing on how various dimensions of market efficiency affect stock prices as measured by Tobin's Q. The following hypotheses are proposed:

Hypothesis 1: Market Efficiency and Stock Mispricing

H_0: There is no significant relationship between market efficiency and the degree of stock mispricing.

H_1: Greater market efficiency is associated with a reduction in stock mispricing, leading to stock prices that are more closely aligned with their intrinsic values.

Hypothesis 2: Stock Turnover and Fair Value

H_0: Stock turnover has no significant effect on the fair value of stocks as measured by Tobin's Q.

H_1: Higher stock turnover is positively associated with the fair value of stocks, indicating that increased trading activity enhances market efficiency and aligns prices with intrinsic values.

Hypothesis 3: Trading Volume and Fair Value

H_0: Trading volume does not significantly impact the fair value of stocks as measured by Tobin's Q.

H_1: Increased trading volume is positively correlated with the fair value of stocks, suggesting that higher liquidity improves market efficiency and reduces mispricing.

Hypothesis 4: Market Capitalization and Fair Value

H_0: Market capitalization as a percentage of GDP has no significant effect on the fair value of stocks.

H_1: Greater market capitalization as a percentage of GDP is positively associated with the fair value of stocks, indicating that a larger market capitalization enhances overall market efficiency and better aligns stock prices with their intrinsic values.

These hypotheses are formulated to test the relationship between various aspects of market efficiency and the fair value of stocks. The results of this research will provide insights into how different facets of market efficiency impact stock pricing and contribute to a deeper understanding of financial market dynamics.

4/ Scope of the Research:

I. Objective Constraints:

Data Availability: The analysis will be constrained by the availability and quality of data on stock market turnover, volume, market capitalization, and Tobin's Q.

Market Efficiency Measurement: The study will focus on specific indicators of market efficiency, such as stock turnover, volume, and market capitalization, and will not encompass all possible measures of efficiency, such as insider trading or regulatory quality.

Scope of Stock Valuation Metrics: The study will use Tobin's Q as the primary measure of stock valuation. Other valuation metrics, such as Price-to-Earnings ratios or Book-to-Market ratios, will not be covered in this study.

Analytical Methods: The study will utilize regression analysis and related statistical methods to test the hypotheses. Limitations in the chosen methods or statistical models may affect the interpretation of results.

II. Geographic Scope:

The research will encompass both emerging and developed markets to compare how market efficiency affects stock valuation across different economic environments. Specific countries or regions will be selected based on data availability and relevance.

III. Chronological Boundaries:

The study will focus on data from the period between 2004 and 2022 to capture both historical trends and recent developments in market efficiency and stock valuation. This timeframe allows for an analysis of how market efficiency impacts stock valuations over an extended period, encompassing various economic cycles and market conditions.

5/ Methodological Framework:

The study utilizes a descriptive approach to elucidate the theoretical framework surrounding the relationship between the study variables and existing literature. Additionally, it employs an inductive method to examine the phenomenon of stock market efficiency and the fair value of stocks. This involves gathering and analyzing all relevant data and information available during the study period to derive general principles from specific details. The study also considers the findings and recommendations of prior research to inform the proposed research topic.

6/ Theoretical Framework and Previous Studies:

The intersection of market efficiency and stock valuation is a critical area of study within financial economics, impacting both theoretical discourse and practical investment strategies. Market efficiency, a concept deeply rooted in the Efficient Market Hypothesis (EMH), postulates that asset prices fully reflect all available information at any given time. This foundational theory, initially proposed by Eugene Fama in the 1960s, has evolved through various forms, including weak, semi-strong, and strong efficiency, each describing different degrees of information incorporation into stock prices.

Understanding market efficiency is essential for evaluating stock fair value—an intrinsic measure of a stock's worth based on fundamentals such as earnings, dividends, and growth prospects. When markets are efficient, the fair value of stocks should, theoretically, align with their market prices. Conversely, deviations between market prices and fair values can indicate inefficiencies, leading to potential arbitrage opportunities or mispricing.

Theoretical frameworks exploring this relationship often draw on models like the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT), which offer insights into how information and risk factors influence stock prices and valuations. These models provide a structured approach to understanding how different levels of market efficiency affect stock pricing mechanisms.

Previous studies have examined the impact of market efficiency on stock valuation across various global markets, including emerging and developed economies. Research has shown that market efficiency can vary significantly depending on the market's maturity, regulatory environment, and the quality of available information. In emerging markets, such as those in Arab countries, unique challenges and characteristics—such as lower market liquidity, less transparent financial reporting, and varied regulatory frameworks—can influence the degree of market efficiency and, consequently, the accuracy of stock valuations.

The study of Fama (1970) is a cornerstone of financial economics. In this influential review, Fama systematically examines the Efficient Market Hypothesis (EMH), which asserts that asset prices in capital markets fully reflect all available information at any given time. Fama concluded that capital markets are efficient in processing information. Specifically, stock prices reflect all available information, meaning that it is impossible to consistently achieve returns higher than the market average through stock selection or market timing. This implies that fair value is quickly and accurately reflected in stock prices.

Chen, Roll & Ross (1986) investigated the influence of macroeconomic factors on stock market returns. The paper explored how various economic variables impact stock prices and the overall performance of the equity market. The study found that economic forces, such as inflation and interest rates, significantly impact stock prices and returns. Their research supported the idea that while market prices often reflect these economic factors, there are still periods where prices may deviate from fair value due to market inefficiencies.

In another study, Fama & French (1992) introduced a new asset pricing model that extends the Capital Asset Pricing Model. They identified several factors that explain variations in stock returns, including size and book-to-market ratios. They found that market efficiency is reflected in these factors, but the study also indicated that some predictable patterns in stock returns exist, challenging the notion of perfect market efficiency.

Jegadeesh & Titman (1993) investigated the profitability of momentum trading strategies and their implications for the Efficient Market Hypothesis (EMH). They discovered that momentum strategies—buying stocks that have performed well in the past and selling those that have performed poorly—yielded positive returns. This finding suggests that markets are not perfectly efficient as such strategies can generate excess returns, indicating that stock prices do not always fully reflect all available information.

In his paper, “Market Microstructure and Stock Return Predictability,” Harris (1997) explored the relationship between market microstructure—the study of how trades and quotes affect stock prices—and the ability to predict stock returns. Harris's research revealed that market microstructure elements, such as trading volume and bid-ask spreads, affect stock return predictability. The study highlighted that while markets are generally efficient, microstructural factors can create short-term inefficiencies affecting stock valuation and returns.

Shiller (2000) paper, “Measuring Bubble Expectations and Investor Confidence,” provides a critical analysis of the role of investor sentiment in financial markets, particularly focusing on how expectations of market bubbles influence asset prices. Shiller found that investor expectations and confidence play a significant role in stock price movements, sometimes leading to deviations from fair value. His research suggests that psychological factors and market sentiments can cause stock prices to diverge from their fundamental values, indicating inefficiencies in the market.

In their paper, “Uniformly Least Informative Anomaly: The Case of Earnings Announcement Returns,” Loughran and Ritter (2000) explore a significant anomaly in financial markets related to the returns observed following earnings announcements. They demonstrated that earnings announcements have significant effects on stock returns, but the market's reaction can be less informative than expected. The results suggest that while the market is generally efficient, anomalies still exist, particularly in how information is processed and reflected in stock prices.

Bisciari, Durré & Nyssens (2003) analyzed the valuation of the U.S. stock market, focusing on how stock prices are determined and assessed in relation to fundamental economic indicators. They find that traditional valuation models, such as those based on earnings and dividends, have limitations in capturing the full scope of market fluctuations. The paper highlights that while these models offer valuable insights, they may not fully account for market anomalies or investor behavior. The authors suggest that incorporating more comprehensive models and considering macroeconomic factors could improve the accuracy of stock market valuations.

In 2008, Milburn explores the intricate connections among fair value accounting, market value, and the Efficient Market Hypothesis (EMH). He highlighted both theoretical and practical aspects of this relationship, offering insights into the effectiveness and limitations of fair value accounting in reflecting true asset values and supporting market efficiency. Milburn found that fair value accounting, which aims to reflect the current market value of assets and liabilities, generally aligns well with market value. However, he also noted that discrepancies can arise due to factors such as liquidity, market volatility, and estimation methods used in fair value measurement.

In the 2013 paper "Fair Value Accounting and Market Efficiency" presented at the CAAA Annual Conference, Song explores the relationship between fair value accounting and market efficiency. Song found that fair value accounting can enhance market efficiency by providing more accurate and timely information about the value of assets and liabilities. This improved information helps ensure that stock prices better reflect all available information, aligning more closely with the principles of market efficiency.

Buachoom (2022) investigated the interplay between fair value accounting, corporate governance, and stock prices, with a focus on the information efficiency of the Thai stock market. He found fair value accounting has a significant effect on stock prices in Thailand. The study indicates that fair value measurements, by reflecting current market conditions more accurately, contribute to better alignment of stock prices with the intrinsic values of firms.

Recently, Petrović, Radosavac & Mashovic (2023) explored the impact of fair value accounting on contemporary financial reporting practices. The outcomes of their study refers that that fair value accounting enhances the relevance and timeliness of financial information by reflecting current market conditions. However, the study also identifies challenges, such as increased volatility in financial statements and potential difficulties in determining fair values for illiquid assets. The authors conclude that while fair value accounting improves transparency, it requires robust valuation techniques and careful implementation to mitigate its inherent limitations.

In sum, empirical research in this context has revealed mixed results, highlighting the complexity of applying the EMH to diverse market environments. While some studies suggest that stock prices in these markets are relatively efficient, others point to persistent inefficiencies that can impact fair value assessments.

7/ Empirical Results:

7/1/1 Model Overview:

The model sample includes balanced panel data from eight countries (Egypt, Morocco, Tunisia, Saudi Arabia, UAE, Kuwait, Oman, and Qatar) spanning the period from 2004 to 2022. This dataset represents the most comprehensive continuous annual time series available, encompassing a wide range of variables across the selected countries.

The companies selected to represent a specific stock market were chosen using MSCI methodology, which targets a set of companies that collectively account for approximately 70%-85% of the market. Data for each company was gathered from their annual financial statements, while information on closing prices, trading volume, turnover and GDP was sourced from reputable platforms like Bloomberg.

$$TQ_{(i,t)} = \alpha_0 + \beta_1 \cdot VE_{(i,t)} + \beta_2 \cdot TN_{(i,t)} + \beta_3 \cdot MAC_{(i,t)} + u_{(i,t)} \quad \text{(Eq.1)}$$

Which,

α_0: The constant term in the model,

$u_{(i,t)}$: The random error term,

β: Coefficients of the independent variables in the model,

i,t: i represents the country, and t represents the time period,

$TQ_{(i,t)}$: Tobin's Q, the dependent variable in the model, representing the fair value,

VE: Stock market volume, an independent variable that indicates stock market efficiency,

TN: Stock market turnover, another independent variable representing stock market efficiency,

MAC: Stock market capitalization as a percentage of GDP, an independent variable reflecting stock market efficiency.

In 1969, Nobel Prize-winning economist James Tobin introduced the ‘Q’ ratio. He defined the ‘Q’ ratio as a firm’s market value relative to its assets’ replacement cost as presented in equation No.2:

$$\text{Tobin's Q} = \frac{\text{Market value of firm}}{\text{Replacement cost of firm's assets}} \quad \text{(Eq.2)}$$

A low Tobin’s Q (between 0 and 1) indicates that the market values the company’s assets less than their book value, suggesting the company may be undervalued, including its stock. On the other hand, a high Tobin’s Q (greater than 1) implies that the firm's stock is overvalued, as its market value exceeds the cost of replacing its assets. In such cases, firms are incentivized to invest more in capital since the assets are worth more than their acquisition cost. (Tobin, 1969)

The Lindenberg and Ross (1981) method, commonly used to calculate Tobin's q, is resource-intensive due to its high data demands and the complexity of its computations. The specific calculation procedure for Tobin's q using the L-R method is detailed as follows in equation No.3:

This version highlights the cost and effort associated with the L-R approach.

$$\mathrm{L} - \mathrm{R}q = \frac{\mathrm{PREFST+VCOMS+LTDEBT+STDEBT-ADJ}}{\mathrm{TOTASST-BKCAP+NETCAP}} \quad \text{(Eq.3)}$$

Where:

PREFST is the liquidating value of a firm's preferred stock,

VCOMS is the price of the firm's common stock multiplied by the number of shares outstanding at the close of the year (December 31),

LTDEBT is the value of the firm's long-term debt adjusted for its age structure, STDEBT is the book value of the firm's current liabilities,

ADJ is the value of the firm's net short-term assets,

TOTASST is the book value of the firm's total assets,

BKCAP is the book value of the firm's net capital stock, and

NETCAP is the firm's inflation-adjusted net capital stock.

Therefore, this computational difficulty, particularly when combined with the potential of q to aid in the analysis of a number of important corporate financial decisions, begs a need to create an accurate approximation of q using basic financial information.

Therefore, Chung and Pruitt (1994) developed an approximation of q, on the other hand, that is extremely conservative with respect to both data requirements and computational effort, approximate q is simply defined as follows in equation No.4:

$$\text{Approximate q} = (MVE + PS + DEBT)/TA \quad \text{(Eq.4)}$$

Where:

MVE is the product of a firm's share price and the number of common stock shares outstanding,

PS is the liquidating value of the firm's outstanding preferred stock,

DEBT is the value of the firm's short-term liabilities net of its short-term assets, plus the book value of the firm's long- term debt, and TA is the book value of the total assets of the firm.

(D = AVCL+ AVLTD – AVCA where, AVCL is the accounting value of the company’s current liabilities (taxes payable + short term debt), AVLTD is the accounting value of the long-term liabilities (long term debt), and AVCA is the accounting value of the current assets (cash + receivables)).

As stated above, all of these required inputs are readily obtainable from a firm's basic financial and accounting information. Approximate q as defined in Equation (2) differs from L-R's Tobin's q as outlined in Equation (1) primarily in that approximate q implicitly assumes that the replacement values of a firm's plant, equipment, and inventories are equal to their book values. Both techniques explicitly assume that market and book values for short-term debt are identical.

Results of an estimate of the regression of Chung & Pruitt compared to the estimates of Lindenberg & Ross point out that at least 96.6% of the original q is explained by the approximate q.

Table 1. Variables and measures

Variable	Code	Calculation Techniques	Source
Tobin Q	TQ	(MVE + PS + DEBT)/TA	Companys' Financial statements
Volume	VE	Total Number of Shares Bought and Sold during the period	Bloomberg
Turnover*	TN	Total Value of Shares Traded during the period	Bloomberg
Marker Cap as% of GDP**	MAC	Share Price × Total Number of Outstanding Shares / GDP	Bloomberg & the Worldbank

* We used Value-Based Turnover which Shows how much trading activity happened in terms of money.

** Market Cap: Shows how much a company is worth in total.

Source: Prepared by the researcher.

7/1/2 Research Outcomes:

This section details the experimental outcomes of the tests conducted in the study. It includes a unit root test, using the best method to assess the stationarity of the variables, and a correlation analysis to check for multicollinearity among the independent variables. Additionally, it covers the descriptive statistics of the model variables and uses regression analysis to estimate how Market efficiency affects per fair value of the stock.

Before we delve into statistical tests, it’s worth mentioning that we used the logarithmic form of the variables. As log transformations are frequently used in econometric analysis to address issues related to the distribution of variables and the interpretation of coefficients. By transforming a variable into its logarithmic form, researchers can often mitigate problems such as heteroscedasticity, non-normality, and nonlinear relationships. Additionally, the coefficients of log-transformed variables can be interpreted as elasticities, providing insights into the percentage change in the dependent variable for a one percent change in the independent variable (Wooldridge, 2016).

- **Unit Root test:**

A unit root test is a statistical procedure used to determine whether a time series variable is stationary or non-stationary. A stationary time series has a constant mean, variance, and autocorrelation over time, while a non-stationary series exhibits trends or cycles. Stationarity is a fundamental assumption in many econometric models. If a time series is found to be non-stationary, it often requires differencing or other transformations to achieve stationarity before proceeding with further analysis (Gujarati & Porter, 2009).

There are various methods to test the stability of a time series. One of the most appropriate, without delving into technical details, is the unit root test, particularly the **Im Pesaran and Shin Test (IPS Test**) and **Levin -lin Chiu Test**.

Levin-Lin-Chiu (LLC) Test: The Levin-Lin-Chiu (LLC) test is a panel unit root test that assumes homogeneity across individual panels. It examines whether a unit root is present in a panel dataset by pooling the information from all individual time series. The LLC test is relatively restrictive as it assumes that the autoregressive coefficient is identical for all cross-sectional units.

Im, Pesaran, and Shin (IPS) Test: In contrast to the LLC test, the Im, Pesaran, and Shin (IPS) test allows for heterogeneity across individual panels. This test is more flexible as it does not impose the restrictive assumption of a common autoregressive coefficient. The IPS test calculates individual unit root tests for each panel and then averages the test statistics to obtain an overall panel test (Maddala & Kim, 1998).

Table 2. Unit root test results

levin-lin chiu Test

Variables	At the level	
	With time trend	No-time trend
	p-value	
LnTQ	0.00	0.00
LnVE	0.00	0.00
LnTN	0.00	0.00
LnMAC	0.00	0.00

IPS Test

Variables	At the level	
	With time trend	No-time trend
	p-value	
LnTQ	0.01	0.02
LnVE	0.00	0.00
LnTN	0.00	0.01
LnMAC	0.00	0.01

Source: Prepared by the researcher using STATA 14 software.

The table No. 2 presents p-values for both tests (IPS & LLC), with and without a time trend. According to this method, the null hypothesis (H_0) states that the time series contains a unit root, meaning it is non-stationary, while the alternative hypothesis (H_1) asserts that the time series is stationary.

Observations:

1. **LnTQ:**

- **LLC Test:** Both with and without time trend, the p-values are 0.00, which is less than both 0.01 and 0.05. This strongly suggests that LnTQ is stationary at both the 1% and 5% significance levels.
- **IPS Test:** The p-values are 0.01 and 0.02, which are less than 0.05 but not 0.01. This suggests that LnTQ is stationary at the 5% significance level but not at the 1% level.

2. **LnVE:**

- **LLC Test:** Both with and without time trend, the p-values are 0.00, which is less than both 0.01 and 0.05. This strongly suggests that LnVE is stationary at both the 1% and 5% significance levels.

- **IPS Test:** Both with and without time trend, the p-values are 0.00, which is less than both 0.01 and 0.05. This strongly suggests that LnVE is stationary at both the 1% and 5% significance levels.

3. **LnTN:**

- **LLC Test:** Both with and without time trend, the p-values are 0.00, which is less than both 0.01 and 0.05. This strongly suggests that LnTN is stationary at both the 1% and 5% significance levels.
- **IPS Test:** The p-values are 0.00 and 0.01, which is less than 0.05 but not 0.01. This suggests that LnTN is stationary at the 5% significance level but not at the 1% level.

4. **LnMAC:**

- **LLC Test:** Both with and without time trend, the p-values are 0.00, which is less than both 0.01 and 0.05. This strongly suggests that LnMAC is stationary at both the 1% and 5% significance levels.
- **IPS Test:** The p-values are 0.00 and 0.01, which is less than 0.05 but not 0.01. This suggests that LnMAC is stationary at the 5% significance level but not at the 1% level.

Overall Interpretation:

Based on both tests, it appears that all variables (LnTQ, LnVE, LnTN, and LnMAC) are likely stationary at the 5% significance level. However, for LnTQ, LnTN, and LnMAC, the evidence for stationarity at the 1% level is weaker based on the IPS test.

The results of the unit root test indicate that we reject the null hypothesis of a unit root in favor of the alternative hypothesis of stationarity. This finding suggests that the time series is stationary, meaning it has a constant mean, variance, and autocorrelation over time.

- **Correlation analysis**

After confirming that the time series for the variables under study are stationary, it's important to ensure there is no multicollinearity among the independent variables before performing the regression. To check for multicollinearity, the correlation matrix between the variables was calculated to determine if there is any linear correlation.

A correlation matrix is a table that displays the correlation coefficients between multiple variables. Each cell in the matrix represents the correlation between two specific variables. Correlation coefficients range from -1 to 1, with values closer to -1 indicating a strong negative relationship, values closer to 1 indicating a strong positive relationship, and values close to 0 indicating little to no relationship. Correlation matrices are essential tools in exploratory data analysis as they provide insights into the relationships between variables before proceeding with more complex statistical analyses (Field, 2018).

As shown in Table No. 3, there is no strong linear correlation between the independent variables, suggesting that multicollinearity is likely not an issue.

Table 3. Correlation matrix results

Variables	Lnve	Lntn	Lnmac
Lnve	1.00		
Lntn	0.65	1.00	
Lnmac	0.16	0.43	1.00

Source: Prepared by the researcher using STATA 14 software.

- **Descriptive statistics**

Table No. 4 presents the descriptive statistics for the study variables covering the period from 2004 to 2022. As per **Tobin Q (TQ),** the data reveal that Morocco and Qatar exhibit the highest average Tobin's Q (TQ) values, at 1.3081 and 1.1776, respectively. This suggests that these countries experience higher market valuations relative to their replacement costs. Conversely, Tunisia and Oman have the lowest average TQ values of 0.4720 and 0.5038, respectively, indicating potential undervaluation or lower investor confidence in these markets. Additionally, Qatar and Saudi Arabia display higher standard deviations of 0.7130 and 0.6580, respectively, reflecting greater variability in market valuations. In contrast, Tunisia and Morocco have lower standard deviations of 0.1345 and 0.2705, respectively, indicating more stable market valuations.

As for **Stock Market Volume (VE),** when examining the average stock market volume (VE), the United Arab Emirates (UAE) has the highest mean value of 8,910,868, followed by Saudi Arabia at 3,382,620. These values reflect more significant trading activity, possibly due to a larger market size or higher investor participation. In contrast, Tunisia (17,972) and Morocco (51,263) have the lowest mean volumes, reflecting lower levels of trading activity. The standard deviation is also highest in the UAE (3,955,468) and Saudi Arabia (1,008,539), indicating greater variability in trading volumes compared to countries like Morocco (22,606) and Tunisia (7,605).

According to **Stock Market Turnover (TN),** Saudi Arabia and the UAE lead in stock market turnover (TN), with mean values of 187,000,000,000 and 52,400,000,000, respectively. These high turnovers indicate more frequent trading of stocks, suggesting greater market liquidity. On the other end of the spectrum, Oman (291,190) and Tunisia (221,103) have the lowest turnovers, pointing to less active trading environments. The standard deviation is most prominent in Saudi Arabia (38,100,000,000) and the UAE (33,700,000,000), indicating a wide range of trading activities, while Tunisia (98,807) and Oman (153,103) show much lower standard deviations.

As per **Market Capitalization as a Percentage of GDP (MAC),** Qatar and Morocco show the highest average market capitalization as a percentage of GDP (MAC) at 0.043% and 0.036%, respectively. This indicates a relatively more significant stock market size in relation to the economy. On the contrary, Tunisia (0.006%) and Oman (0.013%) have the lowest MAC ratios, suggesting smaller market sizes relative to their GDP. The standard deviation is highest in Qatar (0.016%), showing more variability, while Tunisia (0.001%) and Oman (0.005%) have the lowest, indicating more stable market capitalization relative to GDP over the observed period.

Based on the descriptive statistics presented, Gulf countries (Kuwait, Oman, Qatar, Saudi Arabia, and UAE) generally display stronger stock market indicators compared to North African countries (Egypt, Morocco, and Tunisia).

Table 4. Descriptive statistics results

Country	Variable	Observations (Obs)	Mean	Std. Dev.	Min	Max
Egypt	TQ	19	0.62	0.45	0.14	1.82
	VE	19	4,680,300	2,134,351	1,885,243	11,500,000
	TN	19	50,500,000	34,000,000	19,600,000	163,000,000
	MAC	19	0.003%	0.002%	0.001%	0.007%
Kuwait	TQ	19	0.58	0.22	0.34	1.80
	VE	19	5,841,597	3,061,867	2,253,222	13,300,000
	TN	19	3,140,000,000	2,080,000,000	13,200,000	7,850,000,000
	MAC	19	0.037%	0.012%	0.023%	0.065%
Morocco	TQ	19	1.31	0.27	0.92	2.01
	VE	19	51,263	22,606	30,032	98,733
	TN	19	13,500,000	8,103,352	7,458,163	31,100,000
	MAC	19	0.035%	0.006%	0.024%	0.052%
Oman	TQ	19	0.50	0.27	0.19	1.01
	VE	19	1,221,032	376,914	619,152	2,036,320
	TN	19	291,190	153,103	120,670	705,970
	MAC	19	0.013%	0.005%	0.008%	0.028%
Qatar	TQ	19	1.18	0.71	0.63	3.06
	VE	19	2,538,985	992,381	1,393,438	5,308,767
	TN	19	30,300,000	14,700,000	15,300,000	69,900,000
	MAC	19	0.043%	0.016%	0.027%	0.085%
Saudi Arabia	TQ	19	0.87	0.66	0.48	3.10
	VE	19	3,382,620	1,008,539	2,194,825	5,657,865
	TN	19	187,000,000	38,100,000	109,000,000	375,000,000
	MAC	19	0.034%	0.022%	0.019%	0.107%
Tunisia	TQ	19	0.47	0.13	0.25	0.71
	VE	19	17,972	7,605	9,635	36,317
	TN	19	221,103	98,307	76,518	502,613
	MAC	19	0.006%	0.001%	0.003%	0.008%
UAE	TQ	19	0.53	0.25	0.32	1.06
	VE	19	8,910,868	3,955,468	3,683,122	17,100,000
	TN	19	52,400,000	31,700,000	12,800,000	117,000,000
	MAC	19	0.026%	0.009%	0.011%	0.045%

Source: Prepared by the researcher using STATA 14 software.

Regression Analysis Outcomes:

Once it has been confirmed that the time series for the variables under study are stationary at the level and that there is no strong linear correlation among the independent variables, the appropriate econometric model can be selected to conduct the regression analysis.

The current study aims to align with modern trends, build on previous research findings, and incorporate their recommendations. With the growing use of data worldwide and advancements in research and development, academic research, particularly in panel data which combines time series and cross-sectional data, has shifted towards using longer time periods. This study uses a twenty-year period (T = 20) to stay current and minimize measurement issues as much as possible (Baltagi, 2021).

Although the sample size was small (N=8), estimating an independent model for each country was challenging due to the short time series. Therefore, the data for the countries in the study sample was collected into a long-balanced data set (T>N). This cross-sectional time series data set encompasses 152 data points (T = 20, N = 8).

There are several methods to handle time series and cross-sectional data, and the most appropriate one can be selected. One approach is to treat the data as time series and create four separate models for each country. However, this is challenging for reasons previously discussed. The data cannot be treated purely as cross-sectional, as this would strip the model of its dynamism. The study excluded the use of the P-OLS model because it yields biased estimates by ignoring the heterogeneity between the countries. Consequently, using this method would be a mistake in model description (Gujarati, 2011).

There are two common methods for handling cross-sectional time series data: Fixed Effects (FE) and Random Effects (RE). **The Fixed Effects** (FE) approach accounts for differences between countries, which are captured in the fixed term (α_i). This means each country has a unique constant, representing unobserved variables in the model. However, it assumes that these differences—such as individual characteristics, education level, cultural factors, religion, and income level—remain constant over time. This method is illustrated by Equation No. 5, and the regression estimation results are displayed in Table No. 5.

$$Y_{(i,t)}= \alpha_i+BX'_{(i,t)} + \varepsilon_{it} \qquad \text{(Eq.5)}$$

where:

Y_{it}: The value of the dependent variable (tq) for each country (i) in period (t),

X'_{it}: is (Kx1) vector of independent variables (VE - TN - MAC) for country (i) in period (t),

β: is (Kx1) vector of parameters of the independent variables,

α_i: is an intercept that's allowed to vary for each country (i), where $\alpha_i = Z_i'\alpha$,

Z_i': consists of both a fixed and a variable component unique to each country (i), But they are all constant over time (t),

ε_{it}: is the random error term, which is assumed to differ for each country (i) and across time (t).

Additionally, the Fixed Effects (FE) model captures differences between countries that are unrelated to time, such as demographic characteristics, religion, and culture, which are part of Zi' and are not linked to the error term (ε_{it}). Therefore, the parameters estimated using this model are not biased due to the omission of characteristics that remain constant over time (Touny, 2012).

Table 5. Fixed effects model regression results

Lntq	Coefficient	Std. Err.	t	P> |t|	[95% conf. Interval]	
Lnve	-0.03	0.09	-0.37	0.71	-0.21	0.14
Lntn	0.11	0.07	1.60	0.11	-0.03	0.25
Lnmac	0.88	0.07	11.75	0.00	0.73	1.02
_cons	5.73	1.32	4.36	0.00	3.13	8.34
sigma_u: 0.87336227						
sigma_e: 0.30843659						
rho: 0.88910863 (fraction of variance due to u_i)						
F test that all u_i=0:			F(7, 141): 28.15		Prob > F: 0.0000	
Model Summary:						
R-squared (within): 0.5594						
R-squared (between): 0.3738						
R-squared (overall): 0.3124						
F(3,141): 59.68						
Prob > F: 0.0000						
corr(u_i, Xb): -0.8793						

Source: Prepared by the researcher using STATA 14 software.

However, if it's believed that differences between countries might influence the dependent variable, **the random effects (RE)** method is more appropriate. Unlike the fixed effects approach, the RE method assumes that these differences between countries are random and not connected to the independent variables in the model. This method is represented in Equation No. (6), and the results of the regression estimation are presented in Table No. 6.

$$Y_{(i,t)} = \alpha + BX'_{(i,t)} + u_i + \varepsilon_{it} \qquad \text{(Eq.6)}$$

α_i: is the fixed effect,

u_i: is the random error term, which is different for each country (i) but constant across time (t),

ε_{it}: is the random error term, which is assumed to differ for each country (i) and across time (t).

The equation for the random effects method includes two error terms. The first, (u_i), represents the error term for each country and remains constant over time. This method assumes that this first error term is not related to the independent variables in the model, with corr (u_i, X) = 0 as an assumption. The second error term (ε_{it}) varies across countries (i) and over time (t). A key feature of the RE method is its ability to incorporate both time-varying and time-invariant variables, such as demographic characteristics, gender, religion, and culture of each country. Additionally, one advantage of the random effects method is that it allows for generalizing conclusions beyond the sample used in the current model (Baltagi, 2021).

Table 6. Random effects model regression results

Lntq	Coefficient	Std. Err.	z	P> |z|	[95% conf.	Interval]
Lnve	-0.03	0.06	-0.55	0.58	-0.16	0.09
Lntn	0.03	0.05	0.52	0.60	-0.07	0.12
Lnmac	0.78	0.07	10.92	0.00	0.64	0.92
_cons	6.37	1.07	5.97	0.00	4.28	8.46

sigma_u: 0.36100378
sigma_e: 0.30843659
rho: 0.57804287 (fraction of variance due to u_i)

Model Summary:
R-squared (within): 0.5509
R-squared (between): 0.4217
R-squared (overall): 0.3520
Wald chi2(3): 141.62
Prob > chi2: 0.0000
corr(u_i, X): 0 (assumed)

Source: Prepared by the researcher using STATA 14 software.

To determine the most suitable method between the fixed effects and random effects approaches for constructing a regression model, we perform the Specification Test (ST), developed by Hausman. The null hypothesis (H_0): posits that the random effects (RE) model is the best fit, while the alternative hypothesis (H_1): suggests that the fixed effects (FE) model is more appropriate.

It basically tests whether the error term (u_i) (unobserved independent variables in the model) is correlated with the independent variables (X'_{it}) or not. The null hypothesis (H_0) claims there is no statistically significant association, while the alternative hypothesis (H_1) suggests there is a statistically significant association.

This test is conducted by comparing the results of fixed effects and random effects models through the covariance matrix (CM). It involves subtracting the coefficients of all independent variables (subtracting the regression parameters of the fixed effects model from those of the random effects model). If the differences are small and not statistically significant, it suggests that the null hypothesis (H_0) is accepted, meaning there is no statistically significant relationship between the independent variables (X'_{it}) and the error term (u_i). (Hausman, 1978)

It is clear from the results of the Hausman test, shown in Table No.7, that the P-Value of chi2 (0.00) is less than 5% meaning that it is statistically significant at the 5% level of significance. In this case, we reject the null hypothesis and accept the alternative hypothesis, therefore, the appropriate model is the fixed effects model.

Table 7. Hausman test results

	Coefficients			
Variable	**(b) (fixed)**	**(B) (random)**	**(b-B) Difference**	**sqrt (diag(V_b-V_B)) S.E.**
Lnve	-0.03	-0.03	0.00	0.06
Lntn	0.11	0.03	0.09	0.05
Lnmac	0.88	0.78	0.10	0.02

Test: Ho: difference in coefficients not systematic

chi2(3) = (b-B)'[(V_b-V_B)^(-1)] (b-B) = 50.37
Prob>chi2 = 0.0000

Source: Prepared by the researcher using STATA 14 software.

Based on the discussion in this chapter, it is evident that the most suitable approach for this study is to apply a dynamic model to panel data, which combines time series and cross-sectional data. This approach is referred to as **"the Dynamic Cross-sectional Time Series Data Model,"** utilizing the fixed effects (FE) method over the period from 2004 to 2022 in a comparative study between (Egypt, Kuwait, Morocco, Oman, Qatar, Saudi Arabia, Tunisia, and the UAE). The results of the regression estimation using the fixed effects (FE) model are presented in Table No. 8, based on Equation No. 7.

$$Lntq_{(i,t)}=\alpha_i+\beta_1\cdot Lntq_{(i,t-2)}+\beta_2\cdot Lnve_{(i,t)}+\beta_3\cdot Lntn_{(i,t)}+\beta_4\cdot Lnmac_{(i,t)}+\epsilon_{(i,t)} \quad (Eq.7)$$

Where:

$Lntq_{(i,t)}$: the dependent variable for country (i) at time (t),

α_i: The fixed effect specific to country (i), capturing unobserved characteristics that are constant over time (t) for each country,

$Lntq_{(i,t-2)}$: The lagged value of $Lntq_{(i,t)}$ by two periods, capturing past effects on the current dependent variable,

$Lnve_{(i,t)}$, $Lntn_{(i,t)}$, $Lnmac_{(i,t)}$: The independent variables for country (i) at time (t),

β_1, β_2, β_3, β_4: The coefficients that measure the effect of each independent variable on the dependent variable,

$\epsilon_{(i,t)}$: The error term, which varies across countries and time.

Several tests were carried out in Stata to optimize the results and address as many measurement issues as possible. Initially, the regression was conducted without incorporating lagged periods for the independent variables, but this approach did not yield strong or significant results for the model. Consequently, the second lag of the dependent variable (L2.Lntq) was included as an independent variable to achieve a more accurate estimation of the model's results.

This approach is used for several reasons:

- **Addressing Autocorrelation:** In time series data, the residuals (errors) may be correlated across time, a problem known as autocorrelation. By including a lagged dependent variable, the model can mitigate this issue by absorbing some of the autocorrelation into the lagged term, leading to more reliable estimates.
- **Modeling Dynamics:** In dynamic panel data models, where the relationship between variables evolves over time, the inclusion of lagged dependent variables allows the model to reflect these dynamics accurately. It helps in understanding how past outcomes affect future outcomes.

Table 8. Fixed effects model regression results (with inclusion of 2^{nd} lag of LnTQ as dependent variable)

Lntq	Coefficie	Std. Err.	t	P> |t|	[95% conf. Interval]	
Lntq L2.	0.38	0.05	8.14	0.00	0.29	0.48
Lnve	-0.23	0.08	-2.88	0.01	-0.38	-0.07
Lntn	0.22	0.06	3.59	0.00	0.10	0.34
Lnmac	0.47	0.07	6.53	0.00	0.33	0.61
_cons	3.17	1.09	2.91	0.00	1.02	5.32
sigma_u: 68475654						
sigma_e: 23184368						
rho: 89715448 (fraction of variance due to u_i)						
F test that all u_i=0:			F(7, 124): 11.06		Prob > F: 0.0000	
Model Summary:						
R-squared (within): 0.6390						
R-squared (between): 0.5696						
R-squared (overall): 0.4779						
F(4,124): 54.88						
Prob > F: 0.0000						
corr(u_i, Xb): -0.8727						

Source: Prepared by the researcher using STATA 14 software.

When using the Fixed Effects (FE) model in panel data analysis, several statistical issues can arise, complicating the interpretation and validity of results such as **Cross-sectional correlation**. This problem occurs when the error terms across different cross-sectional units (such as countries, firms, or individuals) are correlated, which violates the assumption that errors are independent across entities. The presence of cross-sectional correlation can lead to inefficient estimates, understated standard errors, and inflated t-statistics, thereby increasing the risk of Type I errors. This issue can significantly bias the results of the analysis, making it critical to detect and address it in the model. (Baltagi, 2021, Wooldridge, 2010).

To detect cross-sectional correlation, researchers often use the Breusch-Pagan Lagrange Multiplier (LM) test. This test evaluates whether the residuals from a regression model are correlated across cross-sectional units. If the LM test statistic is significantly higher than the critical value, it indicates the presence of cross-sectional correlation, suggesting that the null hypothesis of no correlation should be rejected. Typically, a p-value less than 0.05 in this test signals that cross-sectional correlation exists, and the severity of the issue increases with higher LM test statistics. (Greene, 2018)

Table 9. Breusch-Pagan LM test results

	e1	e2	e3	e4	e5	e6	e7	e8
e1	1.00							
e2	0.08	1.00						
e3	0.19	0.37	1.00					
e4	-0.09	-0.01	0.44	1.00				
e5	0.35	0.40	0.42	0.03	1.00			
e6	-0.46	0.08	-0.24	-0.01	0.14	1.00		
e7	-0.43	0.07	-0.17	-0.20	0.27	0.66	1.00	
e8	-0.46	0.07	0.01	0.14	0.12	0.77	0.70	1.00

Breusch-Pagan LM test of independence: chi2(28) = 54.993, Pr = 0.0017
Based on 15 complete observations

Source: Prepared by the researcher using STATA 14 software.

Based on table No. 9 which indicates the correlation matrix and the significant **Breusch-Pagan LM test statistic**, we can conclude that there is evidence of cross-sectional correlation in the residuals. The p-value of 0.0017 is highly significant, rejecting the null hypothesis of no cross-sectional correlation. This implies that the errors for different cross-sectional units are not independent, which violates one of the key assumptions of the fixed effects model.

To address cross-sectional correlation in Fixed Effects models, one effective approach is to use **clustered standard errors.** To correct for this, clustered standard errors allow for intra-cluster correlation by adjusting the standard errors to account for possible correlations among residuals within clusters. This method involves aggregating the data into clusters (such as by firm, country, or another relevant grouping) and then calculating robust standard errors that account for correlation within these clusters but assume independence between clusters.

This adjustment helps to produce more reliable hypothesis tests and confidence intervals when dealing with panel data. Therefore, employing clustered standard errors is crucial for ensuring the robustness of statistical conclusions in the presence of cross-sectional correlation (Cameron & Miller, 2015).

Table 10. Fixed effects model results after using cluster standard error

Lntq	Coefficie	Std. Err.	t	P> |t|	[95% conf.	Interval]
Lntq L2.	0.38	0.07	5.74	0.00	0.23	0.54
Lnve	-0.23	0.11	-2.03	0.08	-0.49	0.04
Lntn	0.22	0.08	2.77	0.03	0.03	0.41
Lnmac	0.47	0.14	3.35	0.01	0.14	0.80
_cons	3.17	1.46	2.17	0.07	-0.28	6.62

sigma_u: 68475654
sigma_e: 23184368
rho: 89715448 (fraction of variance due to u_i)

Model Summary:
R-squared (within): 0.6390
R-squared (between): 0.5696
R-squared (overall): 0.4779
F(4, 7): 33.05
Prob > F: 0.0001
corr(u_i, Xb): -0.8727

Source: Prepared by the researcher using STATA 14 software.

In table No.10, after applying clustered standard errors at the country level, the results demonstrate a more conservative and potentially more accurate assessment of the statistical significance of the coefficients. The standard errors increased, which led to higher p-values for some variables, such as Lnve, whose p-value increased from 0.005 to 0.082. This change suggests that the significance of Lnve is less robust than initially indicated without clustering, potentially moving it from statistically significant to not significant at the 5% level. The larger standard errors reflect the adjustment for within-country correlations, which provides a more reliable inference by accounting for possible cross-sectional dependence.

While the coefficients themselves remain unchanged, the clustered errors offer a more realistic picture of the data's variability, thus improving the model's reliability in terms of hypothesis testing. This adjustment highlights that certain variables might not be as significant as previously thought when potential correlations within clusters are ignored.

Another problem that we might face in fixed effects model is **heteroscedasticity**. Stock and Watson (2015) explain that "heteroscedasticity occurs when the error variance in a regression model is not uniform across observations, which can distort standard errors and undermine the reliability of hypothesis tests". In other words, Heteroscedasticity arises when the spread of the residuals, or errors, in a regression model varies depending on the level of an independent variable. This inconsistency in error variance can lead to inefficiencies in estimating the model's coefficients and may compromise the accuracy of statistical tests.

To detect this problem, we use **The Modified Wald test**. which is used to detect heteroskedasticity in panel data models with fixed effects model. This test adjusts for the non-constant variance of residuals across different cross-sectional units, thereby enhancing the reliability of parameter estimates and statistical inferences. (Baltagi, 2008)

Table 11. Modified Wald test results

Test Statistic	Value
chi2 (8) =	22.68
Prob>chi2 =	0.0038

Source: Prepared by the researcher using STATA 14 software.

In table No. 11, since the p-value (0.0038) is less than the conventional significance level of 0.05, we reject the null hypothesis of homoscedasticity. This means there is evidence of groupwise heteroskedasticity in the data.

When heteroskedasticity is present, standard errors may be underestimated or overestimated, leading to incorrect statistical inferences. By using **robust standard errors**, the variance of the residuals is accounted for, providing more accurate coefficient estimates and valid hypothesis testing, even in the presence of heteroskedasticity (Hayes & Cai, 2007).

Table 12. Fixed effects model results after using robust standard error

Lntq	Coefficient	Std. Err.	t	P> |t|	[95% conf. Interval]	
Lntq L2.	0.38	0.07	5.74	0.00	0.23	0.54
Lnve	-0.23	0.11	-2.03	0.08	-0.49	0.04
Lntn	0.22	0.08	2.77	0.03	0.03	0.41
Lnmac	0.47	0.14	3.35	0.01	0.14	0.80
_cons	3.17	1.46	2.17	0.07	-0.28	6.62
sigma_u: 68475654						
sigma_e: 23184368						
rho: 89715448 (fraction of variance due to u_i)						
Model Summary:						
R-squared (within): 0.6390						
R-squared (between): 0.5696						
R-squared (overall): 0.4779						
F(4, 7): 33.05						
Prob > F: 0.0001						
corr(u_i, Xb): -0.8727						

Source: Prepared by the researcher using STATA 14 software.

Table No. 12 shows that, standard errors are generally higher when using robust errors, particularly noticeable in the coefficient for Lntq L2. (from 0.047 to 0.067) while Non-Robust Errors estimates show that standard errors are lower without the robust adjustment, which may lead to artificially inflated t-statistics and potentially misleading significance levels.

P-values are slightly higher with robust errors, but the results remain statistically significant for all variables except Lnve at the 5% level indicating that the significance of Lnve is less robust than initially suggested without the robust adjustment.

With robust errors, the model's F-statistic is calculated as an adjusted value accounting for potential heteroskedasticity, leading to a more conservative estimate of model significance. As the non-robust model reports a higher F-statistic (54.88 compared to 33.05), which can be misleading if the underlying assumptions are violated. The results, though slightly less impressive in terms of significance levels, are more trustworthy as they account for violations of classical assumptions in regression analysis.

We might encounter another issue known as **Multicollinearity**. This occurs when two or more predictor variables in a multiple regression model are highly correlated, meaning that one can be linearly predicted from the others with a substantial degree of accuracy. This high correlation among predictors can lead to unstable estimates of the regression coefficients, making it difficult to determine the individual effect of each variable. As a result, multicollinearity can inflate the standard errors of the coefficients, reduce the statistical power of the regression model, and make it challenging to identify the true relationships between the predictors and the dependent variable. (Mansfield & Helms, 1982)

To address such a problem, we use VIF test. **The Variance Inflation Factor (VIF)** test is a widely used diagnostic tool for detecting multicollinearity in regression analysis. VIF quantifies how much the variance of a regression coefficient is inflated due to the correlation among the predictors. Specifically, a VIF value greater than 1 indicates the presence of multicollinearity, but values exceeding 5 or 10 are often considered indicative of significant multicollinearity problems. By identifying and addressing multicollinearity through the VIF test, researchers can ensure more accurate and reliable regression models. (O'Brien, 2007)

Prior to conducting the Variance Inflation Factor (VIF) test, we performed a standard linear regression analysis in table No.13.

Table 13. linear regression analysis results

Source	SS	df	MS		
Model	27.42	4.00	6.86	F(4, 131):	82.95
Residual	10.83	131.00	0.08	Prob > F:	0.00
Total	38.25	135.00	0.28	R-squared:	0.72
				Adj R-squared:	0.71
				Root MSE:	0.29

Lntq	Coefficie	Std. Err.	t	P> |t|	[95% conf. Interval]	
Lntq L2.	0.56	0.05	11.72	0.00	0.47	0.66
Lnve	-0.08	0.02	-4.82	0.00	-0.11	-0.04
Lntn	0.03	0.01	2.32	0.02	0.00	0.05
Lnmac	0.12	0.03	3.84	0.00	0.06	0.18
_cons	1.34	0.36	3.72	0.00	0.63	2.05

Source: Prepared by the researcher using STATA 14 software.

Table 14. VIF test results

Variable	VIF	1/VIF
Lntn	2.23	0.45
Lnve	1.93	0.52
Lnmac	1.53	0.65
Lntq.L2	1.34	0.75
Mean VIF	**1.76**	

Source: Prepared by the researcher using STATA 14 software.

After running the regression, we perform a Variance Inflation Factor (VIF) test to check for multicollinearity among the predictor variables. The results indicate some multicollinearity in the model. Specifically, the VIF values for Lntn and Lnve show moderate multicollinearity, while Lnmac and Lntq.L2 exhibit low multicollinearity. With an average final VIF of 1.76, which is considered low, the multicollinearity is generally acceptable. Therefore, the results do not require further investigation, and no corrective measures are needed.

8/Conclusion:

After addressing and resolving all issues, we can now begin interpreting the results.

The regression results presented in Table No. 12, utilizing the Fixed Effects Model (FEM) approach, clearly demonstrate the model's validity. The Prob. of F = 0.0001 indicates that the model is statistically robust at the 1% significance level.

Moreover, R^2 of 0.4779 indicates that 47.79% of the total variation in Tobin's Q (fair value) over time is explained by changes in the market efficiency variables (volume, turnover, and market capitalization), considering both within-group and between-group variations. The "within" measure focuses on the variability inside each group, reflecting the effect of changes

over time within the same entity (e.g., companies or countries). The "between" measure focuses on the differences between groups, highlighting how much of the variation in fair value is due to differences in market efficiency between different entities.

The overall R-squared suggests that while market efficiency factors are significant in explaining the fair value of the stock, there is still about 52.21% of the variation in fair value that is not captured by these variables. This might be due to other factors not included in the model, such as macroeconomic indicators, company-specific factors, or global financial trends.

- The indicator **Lntq L2 (Lagged Tobin's Q)** is highly significant at the 1% level, showing a strong positive relationship between past and current values of Tobin's Q, as reflected by the positive coefficient. This means that a 1 unit increase in Tobin's Q from two periods ago results in a 0.384 unit increase in the current period's Tobin's Q, assuming other factors remain unchanged. This persistence suggests that market value and replacement cost tend to maintain a consistent trend over time.
- The indicator **Lnve (Volume of the Stock Market),** which reflects market efficiency, is not statistically significant at the conventional 5% level but may be considered marginally significant at the 10% level. This suggests a potential, though not definitive, relationship between market volume and Tobin's Q. The negative coefficient for Lnve indicates that a 1 unit increase in stock market volume could result in a 0.225 unit decrease in Tobin's Q, assuming other variables remain constant. This negative relationship might suggest that higher trading volumes are linked to increased speculative activity or market inefficiencies, which drive the

market value below the replacement cost of assets, thereby leading to a lower fair value.

- The indicator **Lntn (Stock Market Turnover),** representing market efficiency, is statistically significant at the 5% level, reinforcing the notion that turnover plays a crucial role in influencing the market's fair value. The positive coefficient for Lntn indicates that a 1 unit increase in stock market turnover is associated with a 0.219 unit rise in Tobin's Q, assuming other factors remain constant. This positive relationship suggests that higher turnover, typically a sign of liquidity and active trading, has a beneficial impact on the market's fair value compared to the replacement cost of assets.
- The indicator **Lnmac (Market Capitalization),** representing market efficiency, is statistically significant at the 5% level, indicating a strong and reliable relationship between market capitalization and Tobin's Q. The coefficient for Lnmac is also positive, indicating that a 1 unit increase in market capitalization leads to a 0.467 unit increase in Tobin's Q, holding other variables constant. This strong positive relationship suggests that as the market capitalization grows, so does the market's fair value relative to the cost of replacing its assets, which may reflect greater investor confidence and market efficiency.

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