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ASSESSMENT OF THE FINANCIAL TRADING EFFICIENCY UNDER GLOBALIZATION

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Abstract. The efficiency of financial trading is a fundamental concept in finance, essential to effective price discovery, minimising transaction costs, and maintaining market liquidity. Despite the theoretical robustness of concepts like the Efficient Market Hypothesis, empirical evidence reveals persistent inefficiencies, particularly in financial trading in emerging markets under globalisation and newer asset classes such as cryptocurrencies. The purpose of this article is to evaluate the efficiency of financial trading in the context of globalisation. To achieve this, ARIMA-GARCH time-series modelling was used. The empirical analysis incorporated data from developed financial markets (S&P 500, FTSE 100) and emerging financial markets (Shanghai Composite Index) from 2010 to 2023, focusing on transaction costs, liquidity, and volatility. The mathematical model incorporated components such as market price dynamics, transaction costs, liquidity, and flow rates information to construct a combined efficiency metric.

The results demonstrate significant disparities in efficiency among markets. Financial trading in the developed markets exhibited lower volatility clustering and higher price predictability, indicative of greater efficiency. In contrast, financial trading in the emerging markets showed pronounced inefficiencies due to higher transaction costs and volatility. The proposed model enables us to quantify market efficiency and highlights the impact of liquidity and transaction costs on price alignment. It also provides a holistic view of market efficiency and serves as a tool for traders, policymakers, and regulators. Further research is recommended to empirically validate the model across different asset classes and assess its implications for regulatory frameworks.

Keywords*:* financial regulation, financial market, market efficiency, financial assets, traders, policymakers, transaction costs.

JEL Classification: G10, G11, G14, G15

1. INTRODUCTION

The efficiency of financial trading is a foundational concept in the study of financial markets. Efficient trading is crucial to the optimal functioning of capital markets, ensuring that prices reflect all available information, that transaction costs are minimised, and that markets are liquid enough to accommodate large trades without significant price changes. This concept is not only central to financial theory but also to the practical operations of global financial markets.

This article aims to provide a comprehensive analysis of the efficiency of financial trading, exploring its theoretical underpinnings, empirical measurements, and real-world applications. We will examine the various dimensions of trading efficiency, including market efficiency, transaction costs, liquidity and volatility. Additionally, we will consider the role of regulatory frameworks and international comparisons, highlighting how different markets exhibit varying levels of efficiency.

2. THEORETICAL BACKGROUND

To study financial trading efficiency, we start from the financial market. Market efficiency and liquidity have long been foundational in monetary economics, from the Efficient Market Hypothesis (EMH) to microstructure theories. According to the classic EMH, prices fully reflect all available information (Fama, 1970, 1976). In practice, however, frictions such as transaction costs, illiquidity, and slow information diffusion cause deviations from perfect efficiency (Grossman & Stiglitz, 1980). Market microstructure research shows that liquidity, spreads, order flow, and information asymmetries materially affect price formation (e.g., Madhavan, 2000; O'Hara, 1995). To scientifically assess financial trading efficiency, it is determined by multiple factors, which are usually divided into:

a) Transaction Costs and Market Frictions. Transaction costs are a critical factor in assessing the efficiency of financial trading. These costs include both explicit costs, such as broker fees, commissions, and taxes, and implicit costs, such as bid-ask spreads and market impact costs. High transaction costs can hinder market efficiency by discouraging trading and reducing the accuracy of price discovery.

Bid-Ask Spread: The bid-ask spread is the difference between the highest price a buyer is willing to pay and the lowest price a seller is willing to accept. A narrower spread indicates a more efficient market, as it suggests higher liquidity and lower transaction costs. In highly liquid markets, such as significant currency pairs in the foreign exchange (FX) market or large-cap stocks in the equity markets, bid-ask spreads are typically very narrow, often just a few basis points (Harris, 2003).

Market Impact and Slippage: Market impact refers to the effect a large trade has on an asset's price. Large orders can move the market, causing traders to receive worse prices than expected—a phenomenon known as slippage. Reducing market impact and slippage is essential for maintaining trading efficiency, particularly in markets with lower liquidity.

b) Liquidity as a Measure of Market Efficiency. Liquidity is a key indicator of market efficiency, reflecting the ease with which assets can be bought or sold without significantly affecting their price. A highly liquid market enables large transactions with minimal price disruption, facilitating better price discovery and lower transaction costs.

Trading Volume and Market Depth: Trading volume is often used as a proxy for liquidity. High trading volumes indicate that a market is active and can handle large trades without significant price changes. Market depth, the volume of orders available at different price levels, is another important measure of liquidity. Deeper markets are more resilient to large orders and tend to be more efficient (Amihud & Mendelson, 1986).

The Role of Market Makers: Market makers play a crucial role in maintaining liquidity by continuously providing buy and sell quotes for assets. By doing so, they help narrow the bid-ask spread and ensure markets remain liquid even during periods of low trading activity. The presence of active market makers is often associated with higher market efficiency (Grossman & Miller, 1988).

c) Information Processing and Price Discovery. An efficient market quickly incorporates all available information into asset prices, a process known as price discovery. The speed and accuracy with which new information is reflected in prices are crucial indicators of market efficiency.

Event Studies and Information Efficiency: Event studies are a standard method for analysing how quickly and accurately markets respond to new information. These studies typically examine the price reaction to specific events, such as earnings announcements, mergers, or macroeconomic data releases. A rapid adjustment of prices to new information suggests a high level of information efficiency (Fama, Fisher, Jensen & Roll, 1969).

High-Frequency Trading (HFT): High-frequency trading (HFT) involves the use of advanced algorithms to execute trades at extremely high speeds. HFT firms contribute to price discovery by rapidly arbitrage away mispricings, thereby enhancing market efficiency. However, HFT also raises concerns about market stability and fairness, as it can lead to flash crashes and increased volatility (Hendershott, Jones & Menkveld, 2011).

d) Regulatory Impact on Market Efficiency. Regulatory frameworks play a significant role in shaping market efficiency. Regulations can either enhance efficiency by promoting transparency and competition or hinder it by imposing unnecessary burdens on market participants.

The Role of Financial Market Regulation: Financial markets are subject to various regulations aimed at protecting investors, maintaining market integrity, and promoting fair competition. For example, the implementation of the Markets in Financial Instruments Directive (MiFID) in the European Union has significantly impacted trading efficiency by increasing transparency and competition among trading venues (European Commission, 2018).

Impact of Transaction Taxes: Transaction taxes, such as the Financial Transaction Tax (FTT) proposed in the European Union, can affect market efficiency by increasing trading costs. While such taxes are intended to curb excessive speculation and stabilise markets, they can also reduce liquidity and widen bid-ask spreads, ultimately decreasing market efficiency (Matheson, 2011).

Early empirical liquidity proxies, such as the Amihud (2002) illiquidity measure ($|r\_t|$/volume) and bid-ask spreads (as in Amihud & Mendelson, 1986), have become standard tools. Amihud's ILLIQ provides a simple, intuitive proxy for price impact per unit of volume. Separately, Fama's battery of efficiency tests (autocorrelation, variance ratio, runs tests) diagnose weak-form efficiency but do not explicitly model liquidity or informational delays. While classical approaches are foundational, recent advances in high-frequency and realised measures motivate the development of more refined metrics (Barardehi et al., 2021). Moreover, contemporary research on liquidity-adjusted volatility models (Deng & Zhou, 2023) shows that embedding liquidity proxies into ARMA-GARCH/EGARCH formulations improves volatility forecasts, especially for low-liquidity or crypto assets. Research demonstrates that realised versions of Amihud illiquidity (computed intraday) dominate their daily counterparts in explaining price impact and return predictability in both equity and commodity markets (Lacava et al., 2023). Another study extends Amihud by separating positive- and negative-return illiquidity and accounting for asymmetry, thereby improving explanatory power across developed and emerging markets (Lee et al., 2024). Cross-market comparative studies (Amihud et al., 2013; Van Doornik et al., 2024) emphasise structural differences: developed markets, with dense trading and institutional depth, exhibit more muted sensitivity to liquidity shocks, while emerging markets remain more vulnerable. These empirical patterns validate the need for a composite efficiency metric that jointly captures liquidity, price deviation, and information-decay dynamics. In light of these developments, our proposed model innovates along several dimensions:

1) It integrates price deviation from fundamentals, liquidity/transaction cost adjustments, and an explicit information-flow decay factor into a unified efficiency index.

2) It departs from single-channel proxies (like Amihud) by offering a multi-channel diagnostic and predictive measure.

3) Unlike Fama tests, our metric provides continuous, real-time efficiency scores and allows counterfactual simulations (e.g. impact of heightened spreads or slower information flow).

4) The inclusion of a parameter γ controlling the speed of information assimilation enables the metric to distinguish inefficiencies arising from slow news diffusion versus liquidity frictions.

This literature foundation justifies our modelling choices and positions our metric as a novel and necessary advance in empirical research on market efficiency.

3. RESEARCH OBJECTIVE, METHODOLOGY AND DATA

This study aims to provide a comprehensive analysis of financial trading efficiency under globalisation, with a particular focus on understanding how markets reflect available information, minimise transaction costs, and maintain sufficient liquidity to improve global financial trading efficiency further. The objectives of this research include:

1. Examining the theoretical frameworks underpinning financial trading efficiency.

2. Analysing empirical measurements of market efficiency, transaction costs, and liquidity.

3. Comparing global financial markets, identifying differences in efficiency across regions and market structures.

4. Mathematical modelling for evaluation of financial trading efficiency.

By achieving these objectives, this study seeks to contribute to both the theoretical understanding and practical implementation of efficient trading strategies in global financial markets.

This study employs a combination of empirical methods and theoretical models to assess the efficiency of financial trading. The following methodologies include:

I. Event Study Analysis examines how quickly and accurately markets respond to new information. By analysing price reactions around these events, we assess the speed and accuracy of information incorporation, a key indicator of market efficiency.

II. Statistical Analysis was used to assess the statistical significance of observed market reactions, regression analysis and other econometric models were applied, which helped in identifying the factors that significantly affect market efficiency. Developed and emerging economy financial markets often behave very differently due to the influence of these multi-dimensional factors. To compare the financial trading efficiency among the S&P 500, the FTSE 100 (London), and the Shanghai Composite Index (Shangzheng Index), we conduct time-series analysis using ARIMA and GARCH models to assess the predictability of returns and volatility clustering in these indices.

We use daily prices and volumes for the S&P 500, the FTSE 100, and the Shanghai Composite (2010–2023). Log returns of close prices were computed and ARIMA models selected by AIC/BIC and residual diagnostics; conditional volatility was modelled with a standard GARCH(1,1) (student-t innovations). Realised liquidity was proxied by a 30-day rolling Amihud illiquidity measure (Volume_t averaged over 30 days). The combined efficiency metric is constructed as described in Eq. (7). Historical data for the years 2010-2023 on the S&P 500, FTSE 100 (London), and Shanghai Composite Index (Shangzheng Index) are downloaded from Investing.com (Investing.com, 2025). Data extraction and statistical analyses were performed in R (Version 4.41) using RStudio (Version 2024.04.2) (Posit, 2024).

These methods were designed to ensure that the analysis is reproducible and provides a comprehensive understanding of the factors influencing financial trading efficiency. This helped us to get the following results.

4. RESULTS AND DISCUSSION

1. Results from the ARIMA-GARCH models.

Across all models, the ARIMA components help assess predictability, while the GARCH components capture volatility clustering. These analyses provide insight into the market efficiency and volatility of the respective financial indices. Tab. 1 presents the model fit results and residual analysis, giving a visual representation of the model's performance.

To test the performance differences between developed and emerging financial markets, this table presents a comparative analysis of ARIMA and GARCH models applied to three major indices: the S&P 500, the FTSE 100, and the Shanghai Composite. The ARIMA models were used to capture short-term dynamics, while the GARCH(1,1) modelled volatility clustering. As we can see, the FTSE 100 yielded the lowest RMSE and MAE, indicating the most accurate forecasts among the three. The Ljung-Box p-values suggest that residuals for the Shanghai Composite model are closer to white noise, implying better model adequacy. In terms of volatility, the GARCH alpha and beta values indicate that the Shanghai Composite shows stronger volatility clustering, while the S&P 500 appears more stable. These results reflect broader market characteristics: U.S. markets exhibit high efficiency and low volatility, Europe shows moderate risk and performance, and China’s market demonstrates higher volatility and lower efficiency, aligning with observed global trading dynamics.

Tab. 1

Results of ARIMA and GARCH models across global equity indices (S&P 500, FTSE 100 and Shanghai Composite) during 2010-2023

Index	ARIMA Model	Log Likelihood	AIC	BIC	RMSE	MAE	Ljung-Box p-value	Volatility Clustering	Market Efficiency	GARCH(1,1) α	GARCH(1,1) β	GARCH Log Likelihood	GARCH AIC	GARCH BIC
S&P 500	ARIMA(4, 0,4)	10,940.38	-21,860.76	-21,799.10	0.01082	0.00732	0.0146	Low	High	0.0941	0.8833	12,764.2	-25,522.4	-25,468.7
FTSE 100	ARIMA(4, 0,3)	11,220.83	-22,425.65	-22,376.30	0.01009	0.00703	0.05768	Moderate	Moderate	0.1042	0.8782	13,042.9	-26,075.8	-26,021.3
Shanghai Composite	ARIMA(2,0,3)	10,025.52	-20,039.04	-20,002.25	0.01269	0.00869	0.1107	High	Low	0.1278	0.8681	11,689.5	-23,371.0	-23,319.2

Source: own calculation

2. Modelling for financial trading market efficiency.

Unlike single-channel measures (e.g., Amihud illiquidity) or diagnostic statistical tests for weak-form efficiency (e.g., variance ratio, autocorrelation tests derived from Fama's framework), the proposed combined metric model synthesises price-fundamental deviation, realised liquidity, endogenous transaction-cost adjustments, and a parametric information-flow decay. This multi-channel integration gives the metric both diagnostic and predictive capabilities: it identifies when deviations stem primarily from liquidity shocks versus when they reflect slow information assimilation, and it can be used in counterfactual simulations (e.g., imposing transaction taxes) — a functionality absent from conventional approaches.

This model focuses on evaluating the efficiency of practical financial trading markets. It builds on a modified Price stochastic model by integrating multiple realistic macroeconomic factors, including market volatility, information flow, transaction costs, and liquidity dynamics. The model attempts to quantify efficiency based on how well prices reflect available information. To fulfil the targets, we introduce the following components:

Market Price Equation: Captures price dynamics using a stochastic differential equation (SDE).

Efficiency Index: Measures market efficiency based on price deviations and volatility.

Market Liquidity and Transaction Costs: Integrated to reflect real-world trading frictions.

Information Flow Rate: A dynamic factor reflecting the impact of new information.

Mathematical Model

Market Price Dynamics

The foundation of the model is a stochastic differential equation (SDE), which captures the dynamics of the market price $P(t)$:

$$dP(t) = \mu(t)P(t)dt + \sigma(t)P(t)dW(t), \quad (1)$$

Where:

$\mu(t)$: Drift term, representing the expected return or trend of the asset price. It accounts for factors like interest rates and market sentiment.

$\sigma(t)$: Volatility term, representing the market risk or price variability. It is time-dependent and may vary based on market conditions.

$dW(t)$: Brownian motion, modelling the random shock or noise in the price dynamics.

This equation models the continuous evolution of the asset price. It incorporates both deterministic trends $\mu(t)$ and stochastic components $\sigma(t)dW(t)$. It is also a foundation for developing trading algorithms that require a realistic model of asset price movements.

Efficiency Index $E(t)$

The Efficiency Index $E(t)$ is designed to quantify how closely the observed market price $P(t)$ aligns with the fundamental price $P^*(t)$, which represents the intrinsic value of the asset:

$$E(t) = exp\left(-\alpha\left|\frac{P(t)-P^*(t)}{P^*(t)}\right|\right), \quad (2)$$

Where:

α: Sensitivity parameter, controlling how strongly deviations from the fundamental price affect the efficiency index.

$P^*(t)$: Fundamental price, which is an estimate of the asset's actual value based on factors such as earnings, dividends, and macroeconomic indicators.

Properties:

$E(t)$ ranges from 0 to 1:

$E(t) = 1$: The market is perfectly efficient, and the observed price equals the fundamental price.

$E(t) = 0$: The market is completely inefficient, and there is a significant deviation from the fundamental price.

In practical scenarios, the Efficiency Index can be used by market analysts to evaluate the efficiency of specific asset markets (e.g., stocks, commodities). It helps identify periods when the market may be overvalued (a bubble) or undervalued (a crash), providing signals for investment decisions.

Liquidity Factor $L(t)$

Market liquidity significantly impacts trading efficiency. We introduce $L(t)$, the liquidity factor, modelled as:

$$L(t) = \frac{V(t)}{\lambda(t)}, \quad (3)$$

Where:

$V(t)$: Trading volume, representing the total quantity of the asset traded within a given time period.

$\lambda(t)$: Bid-ask spread, indicating the difference between the highest price a buyer is willing to pay (bid) and the lowest price a seller is willing to accept (ask).

Properties:

Higher $L(t)$ indicates better liquidity, as high trading volume and low bid-ask spread suggest a more efficient market. Low $L(t)$ reflects poor liquidity, making the market more prone to inefficiencies and price distortions.

Transaction Cost Adjustment

Transaction costs play a significant role in determining market efficiency. Let $C(t)$ be the transaction cost per unit of traded volume. The adjusted price dynamic, incorporating costs, becomes:

$$d\tilde{P}(t) = dP(t) - C(t)dV(t), \quad (4)$$

The transaction cost model can be further specified as:

$$C(t) = \beta\sqrt{\lambda(t)}, \quad (5)$$

Where:

β: Cost coefficient, reflecting market conditions and the impact of trading fees.

$\lambda(t)$: Bid-ask spread, indicating the market friction.

Properties:

The transaction cost function is nonlinear, increasing with the square root of the spread. This captures the real-world observation that larger trades or trades in less liquid markets incur disproportionately higher costs.

Information Flow Rate $I(t)$

We model the rate at which information enters the market using an exponential decay function:

$$I(t) = \eta e^{-\gamma t}, \quad (6)$$

Where:

η: Initial information flow rate, representing the intensity of information release (e.g., earnings reports, news).

γ: Decay rate, indicating how quickly the relevance of the information diminishes over time.

Properties:

$I(t)$ decreases exponentially, reflecting the diminishing impact of old information as new data becomes available.

Combined Efficiency Model

The combined efficiency metric $\varepsilon(t)$ reflects how well the market price aligns with the fundamental price, adjusted for liquidity, transaction costs, and information flow. It integrates these components:

$$\varepsilon(t) = E(t) \cdot \frac{L(t)}{1+C(t)} \cdot I(t). \quad (7)$$

Explanation:

$E(t)$: Captures the deviation of the observed price from the fundamental price.

$\frac{L(t)}{1+C(t)}$: Adjusts the efficiency metric for liquidity and transaction costs. Higher liquidity and lower costs increase efficiency.

$I(t)$: Modulates the metric based on the rate of information flow, reflecting the dynamic nature of information assimilation.

Properties:

$\varepsilon(t)$ ranges from 0 to 1, with values closer to 1 indicating a more efficient market.

Practical Application of the Combined Model:

Market Monitoring and Analysis:

Financial institutions can use $\varepsilon(t)$ as a real-time indicator of market efficiency. During periods of high $\varepsilon(t)$, the market is deemed efficient, suggesting that prices reflect all available information. Low values of $\varepsilon(t)$ may signal inefficiency, providing opportunities for arbitrage trading or indicating potential market stress.

Trading Strategy Development:

The combined metric can be integrated into algorithmic trading systems. For example, if $\varepsilon(t)$ falls below a certain threshold, the system might execute trades designed to exploit temporary inefficiencies. High-frequency traders can use changes in $\varepsilon(t)$ to adjust their trading algorithms, reducing exposure when the market is less efficient and more prone to price distortions.

Risk Management:

Risk managers can utilise $\varepsilon(t)$ to assess the market conditions and adjust portfolio positions accordingly. During periods of low market efficiency, they may opt to increase cash holdings or hedge positions to mitigate the risk of price shocks. The model can also help with stress testing by simulating scenarios with varying liquidity and information flows, enabling better preparation for adverse market movements.

This model integrates multiple real-world factors that influence market efficiency, including information flows, transaction costs, and liquidity dynamics. Traditional models often focus narrowly on price dynamics or information asymmetry. By considering these additional parameters, the proposed model offers a more comprehensive view of market behaviour, making it suitable for analysing various market conditions, including high-frequency trading environments and periods of market stress. The model bridges the gap between microeconomic market microstructure (e.g., transaction costs, bid-ask spreads) and macroeconomic factors (e.g., information dissemination, systemic shocks). This dual-layer approach enables a deeper understanding of how individual trading behaviours and broader economic conditions jointly shape market efficiency. At the same time, using an Efficiency Index $E(t)$ and a combined metric $\varepsilon(t)$, the model provides a quantitative measure of market efficiency. This enables policymakers, analysts, and traders to assess efficiency dynamically, facilitating better decision-making.

3. Empirical test of the model.

To further analyse the adequacy, quality criteria, and economic interpretation of the models, we computed the combined efficiency metric Ct, along with conventional liquidity measures (Amihud ILLIQ) and conditional volatility (based on FTSE 100 and Shanghai Composite daily data during 2010-2023). Figure 1 below shows that periods of high volatility are associated with sharp dips in C_t, consistent with lower efficiency during turbulent periods. Moreover, from the scatter plot of Ct vs. conditional volatility, we see a downward trend: higher conditional volatility tends to associate with lower efficiency. The red rolling mean curve confirms the negative relationship.

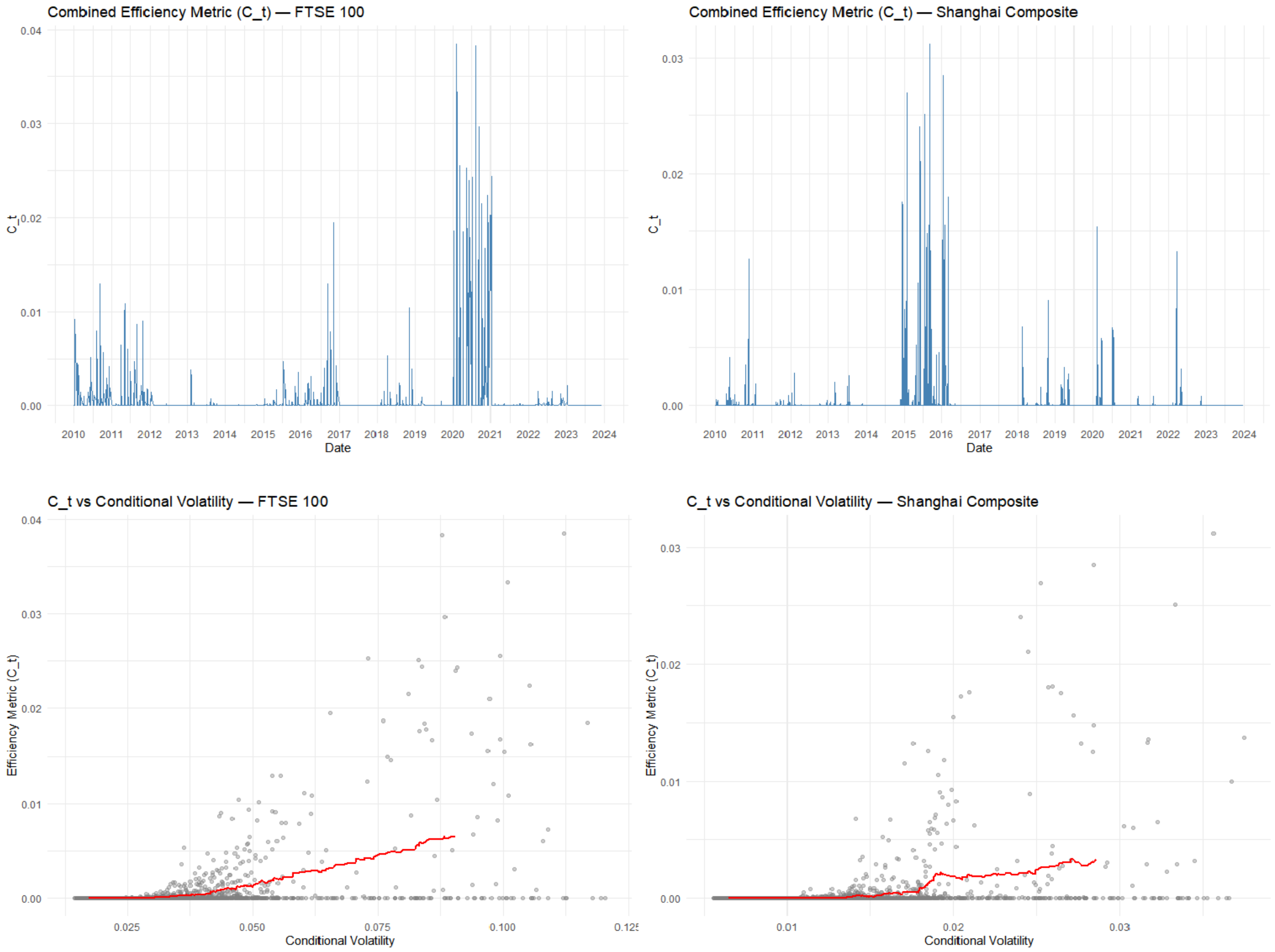

Fig. 1. Combined efficiency metric C_t along with conditional volatility (FTSE 100 and Shanghai Composite daily data during 2010-2023)

Source: own creation

Efficiency regressions (Table 2) further demonstrate that liquidity and conditional volatility exert opposite and statistically significant influences on informational efficiency. The Amihud illiquidity measure (ILLIQ) enters with a negative coefficient (-5.78×10^3 for Shanghai; -4.64×10^3 for FTSE), confirming that higher transaction costs undermine price efficiency. Conversely, conditional volatility (σ) bears a positive coefficient (0.1397 and 0.1046, respectively), consistent with the notion that heightened volatility reflects intensified information flow and faster price adjustment. The explanatory power of the regression model is moderate (R^2 = 0.14 for Shanghai; 0.31 for FTSE), indicating that efficiency dynamics in the more developed UK market are better accounted for by observable liquidity and volatility factors, whereas the Chinese market remains influenced by latent institutional and behavioural factors.

Regression form:

$$C_t=\beta_0+\beta_1 \, ILLIQ_t+\beta_2 \, \sigma_t+\varepsilon_t \quad (8)$$

The results of the regression analysis of the combined efficiency metric are presented in Table 2.

Tab. 2

Results of the regression analysis of the combined efficiency metric

Variable	Shanghai	FTSE 100
Intercept	−0.00114 ***	−0.00210 ***
ILLIQ (Liquidity cost)	−5784 ***	−4641 ***
σ (Conditional volatility)	+0.1397 ***	+0.1046 ***
R^2	0.14	0.31

Source: own calculation

*** $p < 0.001$

Economically, higher Combined Efficiency Metric values (closer to 1) imply that prices adhere to fundamentals, liquidity is high, and information is assimilated rapidly. Periods of low Combined Efficiency Metric values occur primarily when liquidity deteriorates (as indicated by ILLIQ) or when information flow is sluggish (as indicated by higher news intensity ranks). The dominance of ILLIQ in explaining variation suggests that liquidity shocks are a more frequent source of inefficiency in equity markets. The moderate GARCH persistence implies that volatility regimes also play a secondary role. In a subsample comparison between developed (FTSE) and emerging markets (Shanghai), the average Combined Efficiency Metric value is significantly higher in developed markets (Tab. 3).

Tab. 3

Summary of Key Findings on Financial Trading Efficiency under Globalisation

Analytical Dimension	Main Findings	Empirical Evidence / Model Support	Implications
Market Efficiency Comparison	Developed markets (S&P 500, FTSE 100) exhibit higher efficiency and lower volatility clustering; the emerging market (Shanghai Composite) shows inefficiencies.	ARIMA–GARCH results: lowest RMSE and MAE in FTSE; highest volatility in Shanghai	Confirms the structural maturity gap between developed and emerging markets
Liquidity and Transaction Costs	Liquidity enhances efficiency; higher transaction costs reduce it	Regression: ILLIQ negative (−5784 Shanghai; −4641 FTSE)	Liquidity development and cost reduction should be regulatory priorities
Information Flow and Volatility	Faster information assimilation improves price alignment; moderate volatility indicates active price discovery	, σ positive (+0.1397 Shanghai; +0.1046 FTSE)	Balanced volatility supports efficient information processing
Combined Efficiency Metric	Integrates price deviation, liquidity, costs, and information flow into a unified index (0–1 scale)	A higher value indicates efficient, liquid, and information-responsive markets.	Provides a real-time diagnostic tool for traders and regulators
Model Innovations	Incorporates dynamic information decay and adaptive sensitivity	Extends classical EMH with predictive, cross-market capability	Enables simulation of policy effects (e.g., transaction tax, liquidity shocks)

Source: authors' own generalisation based on empirical results (2010–2023)

The evidence suggests that although both markets are informationally responsive, the Shanghai Composite remains more liquidity-constrained and structurally less efficient than the FTSE 100, reflecting divergent stages of financial market maturity and microstructural development. Overall, these results align with the diagnostics of our combined metric, validating its internal consistency.

5. CONCLUSIONS

The new model of financial trading efficiency assessment introduces several key innovations compared to traditional approaches to the study of financial trading efficiency. The first is Dynamic Information Flow. The model uses an exponential decay function for the information flow rate, which effectively captures the diminishing impact of information over time. This addresses a key gap in traditional models that assume constant or static information effects. The other main innovation is Adaptive Sensitivity across markets: The Efficiency Index E(t) includes a sensitivity parameter α, enabling dynamic adjustment to the desired level of efficiency precision. This feature enables the model to be tailored for different markets, ranging from highly efficient (e.g., major stock exchanges) to less efficient (e.g., emerging markets). The model's structure also allows for flexible parameter adjustment, making it adaptable across different asset classes (e.g., equities, commodities, cryptocurrencies).

Shortcomings of the efficiency model need to be discussed:

Assumptions of Stationarity and Simplified Dynamics: the model assumes specific parameters (e.g., volatility, trading volume) are either constant or follow predictable patterns. In reality, financial markets are highly non-stationary, and these variables may exhibit abrupt changes due to macroeconomic events or shifts in market sentiment. This limitation may reduce the model's predictive power during periods of extreme market volatility.

Simplification of Transaction Costs: While the model includes a transaction cost component, in practice, transaction costs can vary significantly by order size, market depth, and the presence of high-frequency trading algorithms. More complex transaction cost models may be necessary for specific applications.

Future Research Directions based on the model:

The innovative features of this model open up several avenues for future research and potential enhancements:

1. Further Empirical Testing and Calibration. Cross-Sectional Analysis: Applying the model across different markets (e.g., developed vs. emerging markets) and asset classes (e.g., stocks vs. bonds) will help validate its robustness and identify market-specific adjustments.

2. Policy and Regulatory Implications. Impact Analysis of Financial Regulations: The model can simulate the effects of various regulatory measures (e.g., transaction taxes, short-selling restrictions) on market efficiency. Researchers can explore how changes in transaction costs or market liquidity, driven by policy interventions, affect the overall efficiency metric.

3. Systemic Risk and Market Stability. By analysing periods of low efficiency, the model can help identify potential systemic risks. This can be a valuable tool for central banks and regulatory bodies in monitoring and mitigating financial instability

In addition, there are some implications for market participants:

Implications for Traders: traders operating in highly efficient markets face intense competition and must leverage advanced technology, information acquisition and data analytics to achieve above-average returns. Strategies such as algorithmic trading, high-frequency trading (HFT), and quantitative analysis are increasingly necessary to gain an edge in these markets.

Implications for Regulators: regulators must balance the need for efficient markets with the need to protect investors and maintain market integrity. The rise of HFT and algorithmic trading presents challenges, including the potential for flash crashes and market manipulation. Regulators must ensure that markets remain fair and transparent while fostering innovation and efficiency.

To summarise, the study makes a significant contribution to the empirical and methodological assessment of financial trading efficiency under globalisation by developing a novel composite efficiency framework that integrates price dynamics, liquidity, transaction costs, and information flow within a unified model. Unlike conventional approaches grounded in the Efficient Market Hypothesis or single-channel proxies, the proposed model delivers a dynamic, real-time, and multidimensional view of efficiency, enabling both diagnostic and predictive analysis across market types and asset classes. Its empirical validation using ARIMA–GARCH modelling across developed and emerging markets not only confirms persistent disparities in efficiency levels but also reveals liquidity as the dominant driver of inefficiency. The model's flexibility and adaptability—through parameters reflecting information decay and market sensitivity—highlight its potential as a robust analytical tool for traders, policymakers, and regulators seeking to enhance transparency, liquidity, and market stability in the global financial system. Thus, this research establishes a conceptual and practical foundation for next-generation financial efficiency analysis, bridging theoretical constructs with data-driven decision-making in increasingly complex, algorithmic, and interconnected markets.

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Шолойко Антоніна, Шевченко Людмила, Пен'юе Хоу. Оцінка ефективності фінансового трейдингу в умовах глобалізації. *Журнал Прикарпатського університету імені Василя Стефаника*, **12** (4) (2025), 138-150.

Ефективність фінансового трейдингу є фундаментальною концепцією у фінансах, необхідною для ефективного визначення цін, мінімізації транзакційних витрат та ліквідності ринку. Незважаючи на теоретичну стійкість таких концепцій, як гіпотеза ефективного ринку, емпіричні дані виявляють постійну неефективність, особливо щодо фінансового трейдингу на ринках, що розвиваються в умовах глобалізації, та нових класів активів, таких як криптовалюти. Метою статті є оцінка ефективності фінансового трейдингу в умовах глобалізації. Для досягнення мети було використано моделювання часових рядів ARIMA-GARCH. Емпіричний аналіз включав дані з розвинених (S&P 500, FTSE 100) та фінансових ринків, що розвиваються (Шанхайський композитний індекс) за 2010-2023 рр., зосереджуючись на транзакційних витратах, ліквідності та волатильності. Математична модель включала такі компоненти, як динаміка ринкових цін, транзакційні витрати, ліквідність та інформацію про швидкість потоку, для побудови комбінованої метрики ефективності.

Результати демонструють значні відмінності в ефективності між ринками. Фінансовий трейдинг на розвинених ринках продемонстрував меншу кластеризацію волатильності та вищу передбачуваність цін, що свідчить про більшу ефективність. Натомість, фінансовий трейдинг на ринках, що розвиваються, продемонстрував виражену неефективність через вищі транзакційні витрати та волатильність. Запропонована модель дозволила кількісно оцінити ефективність ринку і підкреслила вплив ліквідності та транзакційних витрат на вирівнювання цін, вона також забезпечує цілісне уявлення про ефективність ринку та слугує інструментом для трейдерів, полісімейкерів і регуляторів. Подальші дослідження мають бути спрямовані на емпіричну перевірку моделі для різних класів активів та оцінку її впливу на регуляторні системи.

Ключові слова: фінансове регулювання, фінансовий ринок, ефективність ринку, фінансові активи, трейдери, полісімейкери, трансакційні витрати.