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The Dynamics of Capital Structure Measurement Indicators Within the Framework of Market Timing Theory and Their Impact on Improving Banking Performance Efficiency

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ديناميكيات مؤشرات قياس هيكل رأس المال في إطار نظرية توقيت السوق وتأثيرها على تحسين كفاءة الأداء المصرفي

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Abstract **DOI: https://doi.org/10.71207/ijas.v22i88.5719**

The effect of capital structure changes, measured by market timing indicators, on the financial performance of banks - that's, the impact of market timing on profitability as well as on return on assets and return on equity, is examined using banks' size, liquidity ratio, tangible assets ratio and market - to - book ratio as the main independent variables. Based on the combination of the panel data model and the random forest algorithm for analysis, the study finds that a higher market - to - book ratio leads to a significant improvement in banking performance, in line with the tenets of market timing theory, whereas a higher tangible assets ratio has a significant negative impact on banks' profitability. Given the results, the study recommends that managers be alert to market timing opportunities where bank stock price rises, doing so helps improve their financial flexibility and operational efficiency.

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المستخلص

تتناول هذه الدراسة تأثير تغيرات هيكل رأس المال، المُقاس بمؤشرات توقيت السوق، على الأداء المالي للبنوك، أي تأثير توقيت السوق على الربحية، بالإضافة إلى العائد على الأصول والعائد على حقوق الملكية. وتُستخدم في هذه الدراسة متغيرات مستقلة رئيسية، هي: حجم البنك، ونسبة السيولة، ونسبة الأصول الملموسة، ونسبة القيمة السوقية إلى القيمة الدفترية. وبناءً على دمج نموذج بيانات اللوحة مع خوارزمية الغابة العشوائية للتحليل، توصلت الدراسة إلى أن ارتفاع نسبة القيمة السوقية إلى القيمة الدفترية يُحسّن بشكل ملحوظ أداء البنوك، بما يتماشى مع مبادئ نظرية توقيت السوق، بينما يُؤثر ارتفاع نسبة الأصول الملموسة سلبًا بشكل كبير على ربحية البنوك. وبناءً على هذه النتائج، توصي الدراسة المديرين بالانتباه إلى فرص توقيت السوق عند ارتفاع أسعار أسهم البنوك، مما يُسهم في تحسين مرونتهم المالية وكفاءاتهم التشغيلية.

1. Introduction

Capital structure decisions have been one of the most debated topics in finance, especially for banks, whose financial use typically accounts for most of their balance sheet. Traditional capital structure theories like the trade - off theory or pecking order theory generally conclude that firms maintain some specific target debt - to - equity ratio or have a preference hierarchy of financing (Botta, 2024; Chaklader & Chawla, 2016). Yet, the market timing theory by Baker & Wurgler (2002) challenges this traditional static perspective, as it claims that capital structure evolves based on managers' attempts to time the stock market and thus capital structure decisions become a cumulative outcome, not a static decision.

Managers are acutely sensitive to their stock valuations. When stock prices go up, they tend to issue shares, but when prices fall, they often buy back shares or turn to debt. Market timing researchers track managers' activities over time primarily by examining the weighted average market - to - book ratio of their debt issues and equity issues, indicating whether managers' fundraising takes place during market highs (Haddad et al., 2021; Xu et al., 2024). Huang & Ritter (2009) showed that market timing has persistence - i.e., banks which issue stock in a stock boom exhibit low debt - to - equity ratios over several subsequent years and this empirical fact weakens the hypothesis that firms make rapid adjustments to some target capital structure. Instead, firms adjust capital structures - though some slowly and some quickly - according to their successful or unsuccessful market timing activities. Changes in market timing activities affect banks' debt ratios and thus their efficiency as well as their profitability (Dainelli et al., 2024; Nguyen et al., 2021).

Various measures are used to evaluate the banking efficiency: profitability metrics such as return on equity (ROE) and return on assets (ROA) and efficiency metrics including cost - to - income ratio (CIR), among others. Strategic market timing is a way for banks to benefit from mispriced securities and reduce their cost of capital. When banks issue shares at market peak, their Tier 1 capital ratios improve, thereby increasing banks' robustness to uncertainty without having to carry an expensive debt (Harding et al., 2013; Pelizzon et al., 2025). For banks, however, Çelİk & Akarim (2013) believes regulation plays an additional role in market timing strategy, as regulatory capital rules of the Basel III (Bank for International Settlements, 2011) can limit a bank's ability to capitalize on time mispricing and save costs. Thus, market timing for a bank acts not only as an expense - saving tool but also as an effective compliance measure. Building up a bank's capital buffer in a timely manner enhances the bank's ability to extend credit to the economy and boosts its operating efficiency, whereas for a bank, this demonstrates quality management and helps create long - term shareholder value (Jiang et al., 2020; Tasnim et al., 2026).

By considering market timing when evaluating capital structure, a more dynamic and realistic view emerges, with a market - to - book ratio added to the list of performance variables to obtain additional insights. Pandey (2022) indicates that market timing can be used to explain why banks facing similar risks may differ in their capital structure choice. Efficient share timing could give banks increased flexibility and ability to remain competitive and run efficiently in an increasingly integrated financial environment. Welch

(2023) suggest that banks don't avoid restructuring to exploit a timely market opportunity. In particular, Berger & Bouwman (2013) establish that these capital - moving activities relate to banking performance, when prompt decision making plays an essential role.

Market timing theory poses an alternative view on capital structure. It's the idea that managers possess inside information superior to the uninformed outside world and invest by issuing equity at times when investor sentiment is excessive. Overvalued equity shares disconnect from their fundamentals and the cost of equity falls below its intrinsic level. Bank managers then decide to issue stock or sell off portions of the bank at times when the stock price is artificially high. In times of market imbalance, a bank's capital structure is decided not by tax benefits against bankruptcy costs, but by timing the opportunity and the imbalances of the market (Neves et al., 2020). There's an ongoing debate on whether or not a bank's capital structure has a 'memory. Baker & Wurgler (2002) research this phenomenon and propose that capital structures possess a historical stickiness. Past events - such as decisions made when share prices have boomed - still have an effect on the use ratios a bank holds today. For banks, this theory has practical applications.

If a bank decides to issue equity when the stock market is booming, it can construct substantial capital cushions that effectively allow it to forgo issuing additional equity for years. This is directly opposed to the predictions derived from static capital structure models such as the trade - off model, where banks are hypothesized to be continuously adjusting their debt - to - capital ratios towards an average optimal level. However, a different theory of capital structure, labeled the market timing perspective, holds that banks adjust their capital structures strategically, reshaping them to take advantage of temporarily advantageous conditions that the stock market presents. Market timing theory, moreover, reinforces predictions arising from the negative choice theory, an accounting perspective that suggests negative announcements, such as share issuance, likely indicate to the market that a company is overvalued and that managers are selling off equity because it's a good time for them to do so. However, in an overheating market when investors' attention may be captured by excessive exuberance, the negative connotation associated with sending a negative signal is reduced, resulting in a lower penalty to stock price when such an announcement is made. In such a market, a bank can take advantage of share issuing while avoiding the negative impact that'd otherwise have on its stock price, thus increase its regulatory capital and use while retaining operational efficiency and reducing its cost of capital.

In comparison to industrial companies, banks face an additional constraint: minimum required regulatory capital buffers. Therefore, market timing shouldn't only help to increase shareholder value but also allow banks to adjust regulatory minimums for Tier 1 and Tier 2 capital requirements in a cost - efficient manner. During periods when market - to - book ratios are high, banks have an incentive to issue equity capital, which allows them to meet or exceed required regulatory capital levels while simultaneously developing buffers that shield the bank against future credit crises, reduce regulatory risk and may lead to a reduction in the premium demanded by creditors. The bank is described as using market timing in cheap capital contexts to finance loans or investments at rates below market required rates of return to maintain a robust capital buffer, fund loans with lower risk or investment with potentially lower rates or withstand losses without jeopardizing its regulatory capital requirements and thereby achieve higher net interest margins and returns on equity. Various studies have demonstrated such links between skillful market timing behavior and increased technical efficiency.

Despite the growing literature on market timing theory, empirical evidence on its impact on banking performance in emerging economies remains limited, particularly for Iraqi commercial banks, and prior studies have largely relied on linear econometric approaches with limited consideration of nonlinear and interactive effects (Bouteska et al., 2026; Jadah et al., 2025; Mateev, 2025). Accordingly, this study aims to examine the effect of capital structure indicators within the framework of market timing theory on the performance efficiency of Iraqi commercial banks over the period 2005–2024, focusing on bank size, liquidity ratio, tangible assets ratio, and market-to-book ratio in relation to ROE and ROA. The novelty of this research lies in integrating panel data econometric models with Random Forest machine learning to capture both linear and nonlinear relationships, thereby extending prior work that relied mainly on static regression techniques. The study's implications are both theoretical and practical, as it extends market timing theory by highlighting nonlinear dynamics in banking performance and provides evidence to support managerial and regulatory decisions on capital structure, financing timing, and capital buffer management in emerging banking systems.

2. Literature review

2.1. From stability to instability: Capital structure dynamic behavior

While Parsons & Titman (2009) started a "target" view on capital structure, claiming firms behave to a certain target use level, in which taxation benefits from debt are taken against cost of bankruptcy, in finance since the early 2000s research is changing focus towards a "dynamic" model. Banks and firms, than following a "target use" mindset as initially thought, have seen changing use levels determined by several temporary factors. For instance, Flannery & Rangan (2006) introduce an argument about a "partial adjustment" to target use level, where firms want to reach their target ratio but because adjustment costs slows this down, they adjust it to a partial degree and continue to do so gradually. Market timing theory has, then, emerged as one of behavioral explanation for such kind of "unstableness" of firms' use ratios that managers try to maintain a certain level where taxation benefits from debt take against costs of bankruptcy, while still exploiting opportune conditions of capital markets (DeAngelo & Roll, 2016; Flannery & Rangan, 2006).

2.2. Market timing theory as the driving force of dynamism

In this regard, the market timing theory puts managers in charge for timing and adjusting capital structure of firms. Baker & Wurgler (2002) claim that when a bank's market value jumps above its book value, managers have incentives to issue shares thereby reducing debt. When market value drops below the book value, banks either borrow funds or even buy back their own shares thereby raising use ratio. Market - to - book ratio (M/B) is widely utilized to measure whether the market value of the bank is lower than or higher than the value based on accounting figures. This indicator captures market valuation relative to firm fundamentals and suggests that manager behaviour related to the issuance or retirement of shares is sensitive to such shifts, since that they're influenced by the opportunity to maximize shareholder wealth through exploitation of these mispricing conditions. Than relying on a static measure, however, Baker & Wurgler (2002) suggest a time - series measure, called External Finance Weighted Average (M/B), to account for the effects over time. The evidence suggests that timing market movements by a manager will have long lasting effects on the capital structure of the firm. Hence, market timing theory may represent as much an explanation for capital structure dynamics as the pecking order theory, even challenging its premises, as it can explain that sometimes banks directly turn to equity issuance if market conditions are appropriate, effectively jumping steps to maximize the current value of their stock (Setyawan, 2011).

2.3. Banking privacy: Market timing and regulation (Basel III)

In the banking industry, however, regulatory aspects come into play. Banks not only differ from industrial firms in that they're subject to Basel III capital requirements, but also in the sense that, according to recent empirical research hold capital buffers above the minimum requirement to avoid regulatory intervention and ensure operating flexibility (Gropp & Heider, 2010). We provide evidence that they indeed time the market to maintain these capital buffers. These forces are sometimes strong enough to override the regulatory requirements in determining a bank's actual capital level and especially so for more capital - constrained banks. The adjustment speed of capital is also much faster for banks as they may shift both assets and liabilities. However, sometimes the optimal decision based on market timing and the regulatory constraints conflict - for example, during recessions when a bank might want to postpone or forgo stock issues so as not to realize capital losses on their existing assets, yet under regulatory pressure they might feel obliged to sell shares so as not to fail the regulatory requirements. It's thus a composite effect (Francis & Osborne, 2010; Lemma & Negash, 2014).

2.4. Effects on banking efficiency

All these effects attempt to increase efficiency. Following Margaritis & Psillaki (2010), there are three potential channels: (i) cost of capital channel - if a bank is successful in timing the market and sells shares at a peak, its cost of equity decreases. Since banks have significant financial use, even minor cost of capital savings directly boost profit margins and lead to higher returns on equity (ROE) and returns on assets (ROA), (ii) market discipline and agency costs channel - According to Jensen (1986) Free Cash Flow Hypothesis, heavy debt constrains the behavior of managers, reducing wasteful spending. However, market timing may induce banks to reduce their level of debt by issuing stock, thus possibly reducing discipline, therefore, the optimal dynamic relationship involves a balance between timing the market and the disciplining effect of debt and (iii) market value channel (Tobin's Q)-investors may view market timing as an indicator of superior management. When banks successfully time the market, it conveys positive signals to investors, thereby increasing the bank's market value and enhancing its performance.

2.5. Banking performance efficiency

Banks are important to the economic and societal systems as not only shareholder entities with profit - maximizing purposes, but also as stable, resource allocating intermediaries (Berger et al., 2015). Banking performance measurement extends beyond merely accounting ratios to capture how efficiently banks deploy and convert their financial resources under varying regulatory environments (Menicucci & Paolucci, 2016). Performance is viewed as a dynamic process managed in response to volatile market conditions.

Sharma et al. (2013) classified banking performance into technical efficiency - the ability to extract the maximum level of output from a given level of input - and allocative efficiency - the ability to choose the most cost - effective mix of inputs to achieve a given level of output. Anis et al. (2023) highlight efficiency as a crucial factor determining banks' survival and sustainability, arguing that inefficiency leads banks to failure.

The efficiency hypothesis of Khan et al. (2017) argues that profitable and high - performing banks don't receive their superior profits from market power but simply by being more efficient. Their greater efficiency translates to lower costs of operation, achievement of economies of scale in production and service, superior returns and higher capital - adequacy levels. Efficient banks possess the capabilities to time capital markets correctly and to carry out appropriate financial structuring arrangements. An alternative efficiency framework sees superior bank profits as arising from monopoly position and not efficiency. Khan et al. (2018) argued that the Structure - Conduct - Performance (SCP) model suggests that banks in concentrated markets can charge their customers higher prices for financial products, whilst simultaneously paying lower prices on liabilities. This results in higher profits in this type of market structure. But, following widespread liberalization of domestic banking markets worldwide coupled with capital globalization, it's becoming much more difficult for banks to exercise market power in their respective markets. A banks' ability to exercise 'financial intelligence'-such as identifying windows in financial markets to issue equity or secure loans in an opportune fashion - has become a critical attribute of profitable and successful banking (Chen & Liao, 2011).

Among the internal factors, capital structure has been extensively documented to positively affect profitability ratios. This stems from two main reasons: first, debt financing can boost ROE through tax Shields and second, debt forces bank management to act disciplinarianly to cut down on wasteful agency costs and increase operational efficiency through reduced free cash flows (Rao et al., 2019). Berger & Bouwman (2013) put the above logic in the opposite perspective, showing that adequate capitalization enables banks to withstand systemic financial crises by allowing management to remain resilient. From a financial perspective, capital structure not only finances banking activities but also serves as a shock - absorber mechanism against turbulent periods.

Another factor that drags down the efficiency of banks is the extent of their non - performing loans (NPLs). Arnone et al. (2024) indicated that banks burdened with a high level of non - performing loans are forced to divert valuable managerial resources away from the production of credit. Their bad assets not only drain management capacity but also constrain their ability to lend to profitable customers. Consequently, high levels of NPLs are found to adversely and drastically affect banks' profitability performance. Market timing theory postulates that managers of banks issue shares opportunistically in buoyant market conditions, thereby exploiting opportunities that don't persist for a long time (Kalkan, 2025). One reason that managers can exploit such opportunities is because markets may overvalue companies and make equities artificially inexpensive. Another reason relates to behavioral factors among investors, which can make markets irrational. Thus, this theory says that equity issuing should be related not to tax and bankruptcy avoidance considerations but to such opportunistic timing considerations (Bartram et al., 2021; Jagirdar & Gupta, 2024). It's important to address how such market timing concerns persist over time and affect banks' capital structure. For instance, Baker & Wurgler (2002) introduced the idea of the 'memory' effect that affects capital structure in that equity issues made during a previous period of high valuation continue to affect capital structure use many years after the initial event occurred. Consequently, an issue of equity by a bank that's carried out during period of peak equity prices contributes positively to its capital buffers over time, thereby lessening its reliance on external borrowing in a down market and casting doubt on aspects of the dynamic trade - off theory that suggest frequent rebalancing of debt and equity (Kim & Sohn, 2017).

Under the framework of the market timing theory, the negative interpretation that's typically assigned to the issuance of equity no longer holds. Specifically, in buoyant market periods, equity issuing leads to only a slight penalty in terms of expected stock returns. This is because investors either attribute the issuance of equity to strategic reasons related to capitalizing upon market overvaluation or simply become desensitized to the information conveyed by the share issue as the premium associated with information asymmetry is minimal in the face of positive market sentiment (Dissanaike et al., 2014). In these situations, banks can increase their capital buffers to fulfill Tier 1 and Tier 2 capital requirements while maintaining capital costs and keeping operational performance high (Korajczyk & Levy, 2003).

The interaction between market timing and Basel III regulation is considerable. Basel III is a package of reforms designed to improve the resilience of the banking sector to financial and economic shocks. The market timing theory has been identified as one of the main drivers for managers seeking cheap capital (Rubio & Carrasco-Gallego, 2016). Market timing can be applied not only to maximize shareholder value but also strategically to satisfy Basel III capital requirements at the lowest possible cost. Consequently, banks attempt to issue equity and other capital instruments when their market - to - book ratio is highest, building capital buffers, improving their efficiency and also reducing their regulatory risk (Gropp & Heider, 2010). Affordable financing is a major catalyst for efficiency gains. Good market timing allows banks to raise capital below prevailing rates, giving them an excess of cash reserves. Such cash allows banks to increase lending at attractive interest rates, meet financial demands, offset unexpected losses and improve key performance measures, including net interest margin and ROE (Warusawitharana & Whited, 2016). This study examines market timing not as a phenomenon purely of corporate finance but also as a test of the financial intelligence, adaptability and long - term strategic thinking of bank management.

3. Methodology

3.1 Research problems

Banks operate in a tumultuous and informationally asymmetric market, thus, deciding how to finance their operations and structure their capital has long been an intriguing problem. Balance sheet management or sequential financing, however, don't adequately explain how debt ratios keep fluctuating in the current context. The market timing theory argues that bank management tries to capture undervalued shares in market lows by choosing to buy back shares and they attempt to sell undervalued or overvalued shares whenever they're available on the market by choosing equity or debt financing. It states that they exploit market misalignments by issuing new shares when share prices are overvalued and by choosing debt when share prices fall below fundamental value, thereby shifting capital structure continuously. This is the heart of this study. How much is bank practice market timing and how do market timings help in bank efficiency? In this context, we pose the following three research questions:

1. How dynamic are banks' capital structures? Do they exhibit significant fluctuations, measured by the movement in market - to - book ratio or debt ratio?

2. Is there statistical evidence that banks consistently practice market timing in their financial decisions?

3. Does the dynamism of bank capital structures associated with market timing lead to better performance, namely, greater profit abilities, liquidity or lower risks?

3.2 Research objectives

The objectives of the study are addressed in the following sequence. Firstly, the research draws on financial and banking literature to provide a sound theoretical background connecting market timing to banking, showing limitations of traditional models to explain dynamic capital structure of banks. Secondly, the research measures the degree of variations in the capital structure of banks over the period of the study and correlate these with movements in their equity prices. Thirdly, the research critically examines whether market - timing strategies of financing improve performance of banking companies and reduce the cost of capital for banks. The study also provides recommendations on how banks can time their financing activities to bolster their capital buffers and fulfill banking regulations at minimum costs.

3.4 Research significance

The importance of the study stems from several points, especially in the Arab academic literature: The scientific importance of the study are as follows, firstly, it contributes to the literature in the finance field by shifting attention from theoretical models of static capital structure to studies dealing with it given changing factors related to behavior and market mechanisms. Second, it establishes the importance of considering the bank's behavior in relation to other institutions and its economic performance in conjunction with market conditions, providing a conceptual and practical model that future researchers could benefit from. 2. Practical importance: To bank decision - makers. This study aids managers in their decision - making to use the potential of high share prices to generate flexible capital structures and enhance their effectiveness. Additionally, it offers guidance for banks to strategically meet capital requirements of international bodies such as Basel, such as by selecting appropriate times for issuing stock, than resorting to limiting their activities or borrowing at exorbitant costs. To investors and regulators. The results will allow investors to better assess stock prices and to forecast the behavior of banks about funding their operations, which in turn contributes to the promotion of financial stability.

3.5 The scales used in the study

Independent variable: Capital Structure Indicators in the Framework of Market Timing Theory or market timing theory indicators it consists of following indicators (Albahadly & Al-Hashemi, 2023; Baker & Wurgler, 2002; Gropp & Heider, 2010; Jahanzeb, 2013; Lonevskyi, 2021),

1. **Bank size index** = Natural logarithm of assets
2. **Liquidity ratio index** = Current assets / Current liabilities
3. **Tangible assets ratio index** = Fixed assets / Total assets
4. **Market cap to book value ratio index** = Market value of shares / Book value of shares

Dependent variables: Indicators of Banking Performance Ratios which consists of following indicators (Berger & Bouwman, 2013; Mhlongo et al., 2025; Monea, 2016; Yamin et al., 2025),

1. **Percentage of Return on Equity (ROE)** = Net income / Total equity
2. **Return on Assets Ratio (ROA)** = Net income / Total assets

3.6. Panel data stationarity and model type selection (unit root-based specification choice)

To ensure the reliability of the econometric results, the study first examines the stochastic properties of all variables using panel unit root tests. This step is important because non-stationary financial variables may produce biased or spurious regression results if not properly tested. The analysis employs four complementary tests: Levin–Lin–Chu (LLC), Im–Pesaran–Shin (IPS), Maddala–Wu (MW), and Hadri tests. These tests differ in their assumptions regarding cross-sectional homogeneity and allow for a more robust evaluation of stationarity across the banking panel.

The results show that bank size, liquidity, and tangible assets are generally stationary, as confirmed by most of the LLC and MW test statistics. In contrast, the market-to-book ratio and profitability measures (ROE and ROA) display mixed outcomes across tests, indicating sensitivity to market fluctuations, economic instability, and structural changes in the Iraqi banking sector over the study period. The Hadri test further supports the presence of stationarity for most variables, while highlighting variability in financial performance indicators. To complement the unit root analysis, cointegration testing is applied using a Kao-type approach. The results confirm the existence of a long-run equilibrium relationship among the variables, suggesting that although short-run fluctuations exist, the variables move together over time in a stable framework.

Based on these diagnostic results, the study adopts a static panel data modeling approach. Since most explanatory variables are stationary and cointegration is established, there is no empirical requirement for a dynamic panel specification (such as lagged dependent variable models or Generalized Method of Moments estimators). The absence of strong dynamic dependence further supports the use of static estimators. Accordingly, the econometric strategy is defined as follows, a fixed effects model is used for ROE to control for unobserved, time-invariant heterogeneity across banks. A pooled Ordinary Least Squares (OLS) model is applied for ROA due to weaker evidence of cross-sectional heterogeneity in this specification.

3.7 Econometric model specification

This study employs two baseline panel regression models to examine the determinants of banking performance in Iraqi commercial banks. The ROE model is estimated using a fixed effects specification to control for unobserved bank-specific heterogeneity, while the ROA model is estimated using a pooled OLS approach. The estimated ROE fixed effects model is formally expressed as:

$$\mathbf{\widehat{ROE}_{it} = \hat{\alpha}_i + 0.024\,BankSize_{it} - 0.003\,Liquidity_{it} - 1.489\,TangibleAssets_{it} + 0.036\,MarketToBook_{it} + \varepsilon_{it}}$$

The estimated ROA pooled OLS model is expressed as:

$$\mathbf{\widehat{ROA}_{it} = 0.037 + 0.000\,BankSize_{it} - 0.003\,Liquidity_{it} - 0.163\,TangibleAssets_{it} + 0.004\,MarketToBook_{it} + \varepsilon_{it}}$$

Thus, a complete equation for Baghdad Bank is:

$$\mathbf{\widehat{ROE}_{Baghdad,t} = -0.549 + 0.024\,BankSize_{t} - 0.003\,Liquidity_{t} - 1.489\,TangibleAssets_{t} + 0.036\,MarketToBook_{t}}$$

3.8 Panel model selection strategy

The selection of the appropriate panel data estimation technique is based on a series of specification tests to ensure model validity and efficiency. First, the Hausman test is employed to compare fixed effects and random effects estimators, determining whether unobserved heterogeneity is correlated with explanatory variables. Second, the F-test is used to evaluate whether the fixed effects model is preferable to the pooled OLS model by testing for the presence of individual-specific effects. Finally, the Breusch–Pagan Lagrange Multiplier (LM) test is applied to examine whether the random effects model provides a significant improvement over pooled OLS. The combined results of these tests guide model selection. The evidence indicates that the fixed effects specification is appropriate for ROE due to significant bank-specific heterogeneity, while the pooled OLS model is more suitable for ROA, as cross-sectional effects are not statistically significant in this case.

3.9 Diagnostic and robustness checks

To ensure the reliability and statistical validity of the estimated models, several diagnostic tests are conducted. These include the Breusch–Pagan test for heteroskedasticity, the Wooldridge and Breusch–Godfrey tests for serial correlation, the Pesaran cross-sectional dependence test, and the Variance Inflation Factor (VIF) test for multicollinearity. Together, these tests assess whether the classical regression assumptions are satisfied in the panel data framework. The diagnostic results indicate the presence of heteroskedasticity, serial correlation, and cross-sectional dependence in the data. To address these issues and improve estimator robustness, clustered standard errors and heteroskedasticity-consistent (HC1) robust standard errors are applied in all regression estimations.

3.10 Study population and sample

Data collected in this study covers six Iraqi banks whose shares are traded in the Iraq Stock Exchange from among 25 Iraqi banks, the selection was based on the availability of full data that can be used for calculation and analysis. The study sample spans 20 years, from 2005 to 2024.

3.11 Study hypotheses

Based on the theoretical foundations of market timing theory and previous empirical studies on capital structure and banking performance, this study develops a set of hypotheses to examine the relationship between market timing-related capital structure indicators and the performance efficiency of Iraqi commercial banks. The hypotheses specifically investigate whether bank size, liquidity ratio, tangible assets ratio, and market-to-book ratio significantly influence ROE and ROA (Figure 1).

Main hypothesis

H_1: There is a statistically significant impact of capital structure measurement indicators within the framework of market timing theory on banking performance efficiency in Iraqi commercial banks.

Sub-hypotheses

$H_{1\text{-}1}$: There is a statistically significant impact of bank size on return on equity (ROE) in Iraqi commercial banks.

$H_{1\text{-}2}$: There is a statistically significant impact of bank size on return on assets (ROA) in Iraqi commercial banks.

$H_{1\text{-}3}$: There is a statistically significant impact of the liquidity ratio on return on equity (ROE) in Iraqi commercial banks.

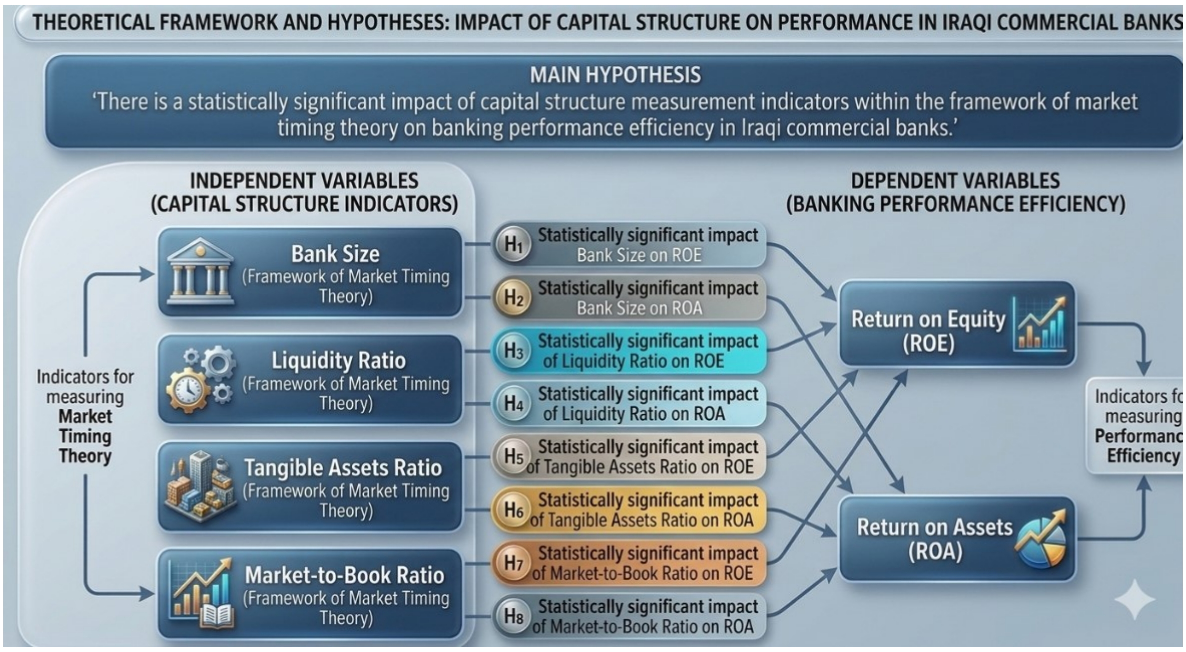
$H_{1\text{-}4}$: There is a statistically significant impact of the liquidity ratio on return on assets (ROA) in Iraqi commercial banks.

H_{1-5}: There is a statistically significant impact of the tangible assets ratio on return on equity (ROE) in Iraqi commercial banks.

H_{1-6}: There is a statistically significant impact of the tangible assets ratio on return on assets (ROA) in Iraqi commercial banks.

H_{1-7}: There is a statistically significant impact of the market-to-book ratio on return on equity (ROE) in Iraqi commercial banks.

H_{1-8}: There is a statistically significant impact of the market-to-book ratio on return on assets (ROA) in Iraqi commercial banks.



Source: Prepared by researchers and using artificial intelligence to improve the appearance

Figure (1) Conceptual framework of the study illustrating the relationship between market timing-based capital structure indicators (independent variables) and banking performance efficiency indicators (dependent variables) in Iraqi commercial banks

4. Statistical analysis and discussion of results

While the decision on how much capital to raise has a lot of important practical consequences for companies, as far as theory on capital structure goes, theory is mostly trailing practice. In terms of the so - called timing market theory, companies don't tend to achieve stable use targets but raise equity at times when stock market prices are high and make use of bank loans when equity prices are low (Baker & Wurgler, 2002). As far as a bank's capital structure is concerned, then time affects the structure much more by market valuations than calculated optimality. The timing market theory seems to oppose the tax - based trade - off theory, whereby banks strive for a balance between tax - related benefits and bankruptcy - related costs, as well as opposes the pecking - order model, where companies resort to financing on the hierarchy of Jahanzeb (2013), suggested bank loans first, followed by convertible debt, then convertible bonds and shares, since there's an information asymmetry where companies know more about their future earnings stream than investors do.

Given the Iraqi bank scenario - where unpredictable events occur, exchange rates fall and regulations are inconstant - we test the market timing theory. This research studies the impact of selected variables - banks' size, liquidity, tangibility and market to book ratio - on banks' performance (ROE and ROA) of 6 Iraqi banks from 2005 to 2024 (Albahadly & Al-Hashemi, 2023).

4.1 Descriptive statistics

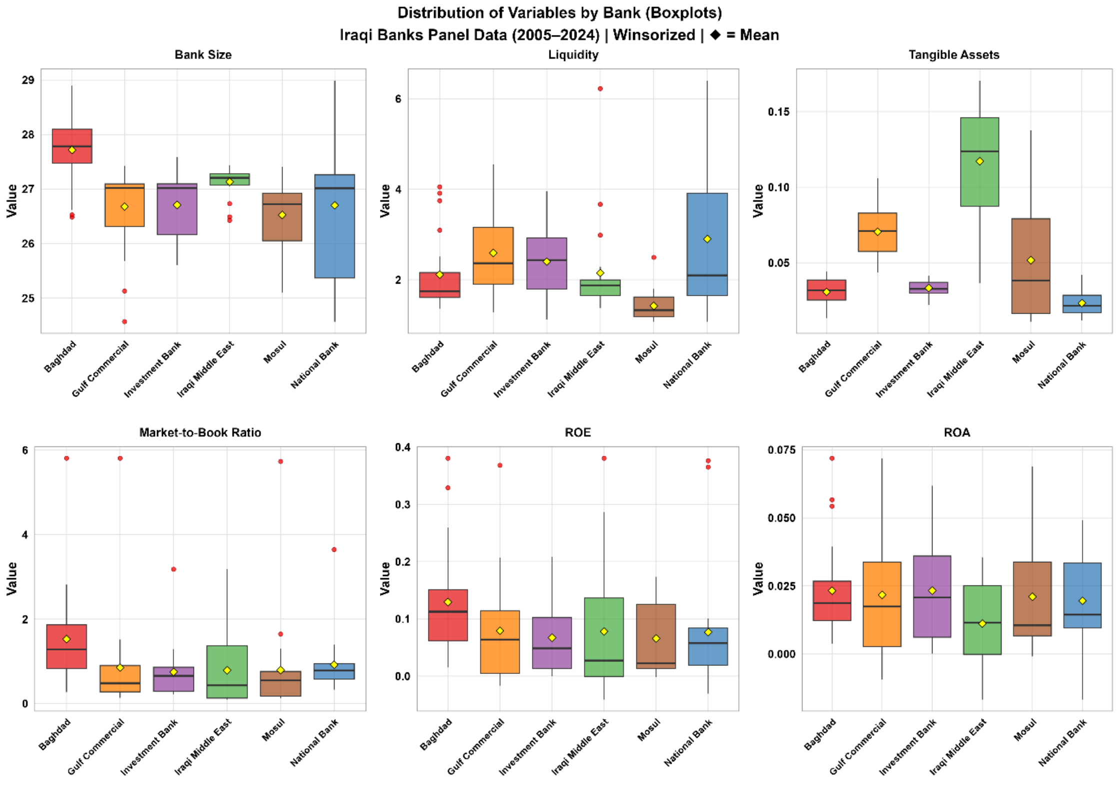
Based on the table, it looks like size can be seen as pretty stable, size mean, log of assets, is 26.91 with a standard deviation of 0.894 (Table 1). This view changes if you look closer at individual bank data. It's possible to notice that Baghdad Bank is way ahead of others, Mosul Bank is at the bottom and National Bank shows the widest fluctuation in size. While it could look like some banks are consistently growing larger with assets, others grow far less with their asset.

Table (1) Descriptive statistics of capital structure indicators and banking performance variables for Iraqi commercial banks (2005–2024)

Variable	N	Mean	SD	Min	Median	Max
Bank size	120	26.910	0.894	24.568	27.066	28.991
Liquidity	120	2.264	1.102	1.073	1.869	6.407
Tangible assets	120	0.054	0.041	0.011	0.039	0.171
Market to book	120	0.938	1.026	0.097	0.744	5.804
ROE	120	0.083	0.094	-0.041	0.063	0.380
ROA	120	0.020	0.020	-0.017	0.016	0.072

N=sample number; SD= standard deviation; Min= minimum range; Max= maximum range; ROE = return on equity; ROA = return on assets; source: prepared by researchers

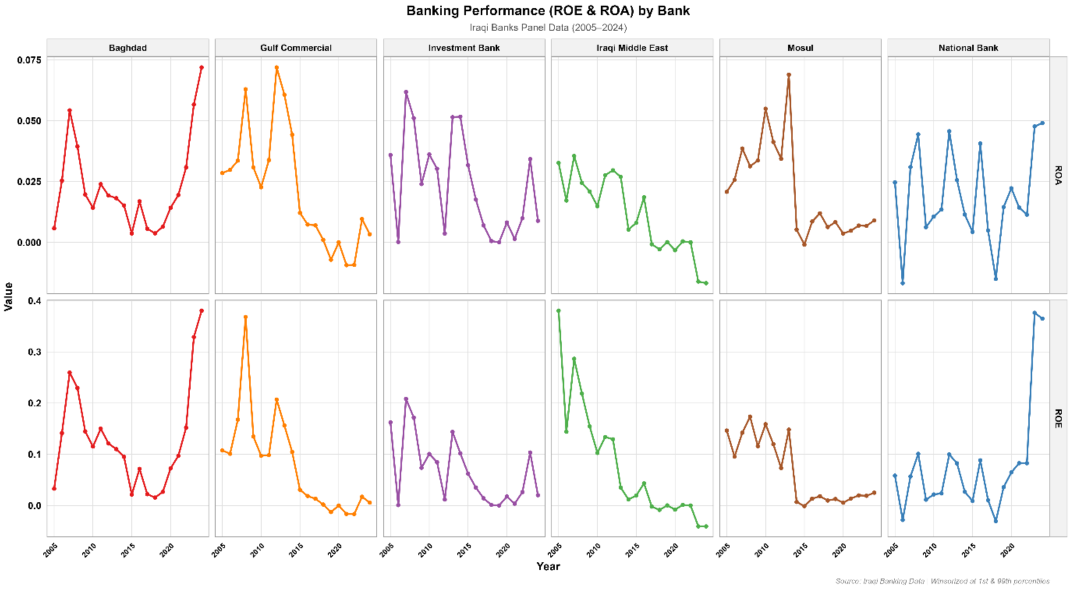
Liquidity ratios (mean 2.26) vary greatly. Gulf Commercial and National Banks usually stand higher than the average for most of the period, indicating their cash reserves fluctuate than being closely controlled. Tangible assets are small on average (0.054), however, Iraqi Middle East Bank has a fourfold greater mean than Baghdad Bank in this category, clearly noticeable from Figure 2. The average market - to - book ratio (0.938) is near the average and doesn't show frequent spikes, except in occasional, drastic periods. Baghdad Bank has a higher average than other banks, which can reflect higher stock valuation periods leading to increased equity sales - a scenario suggested by Baker & Wurgler (2002).



Source: Prepared by researchers using R-STUDIO software

Figure (2) Distribution of capital structure and banking performance variables across Iraqi commercial banks

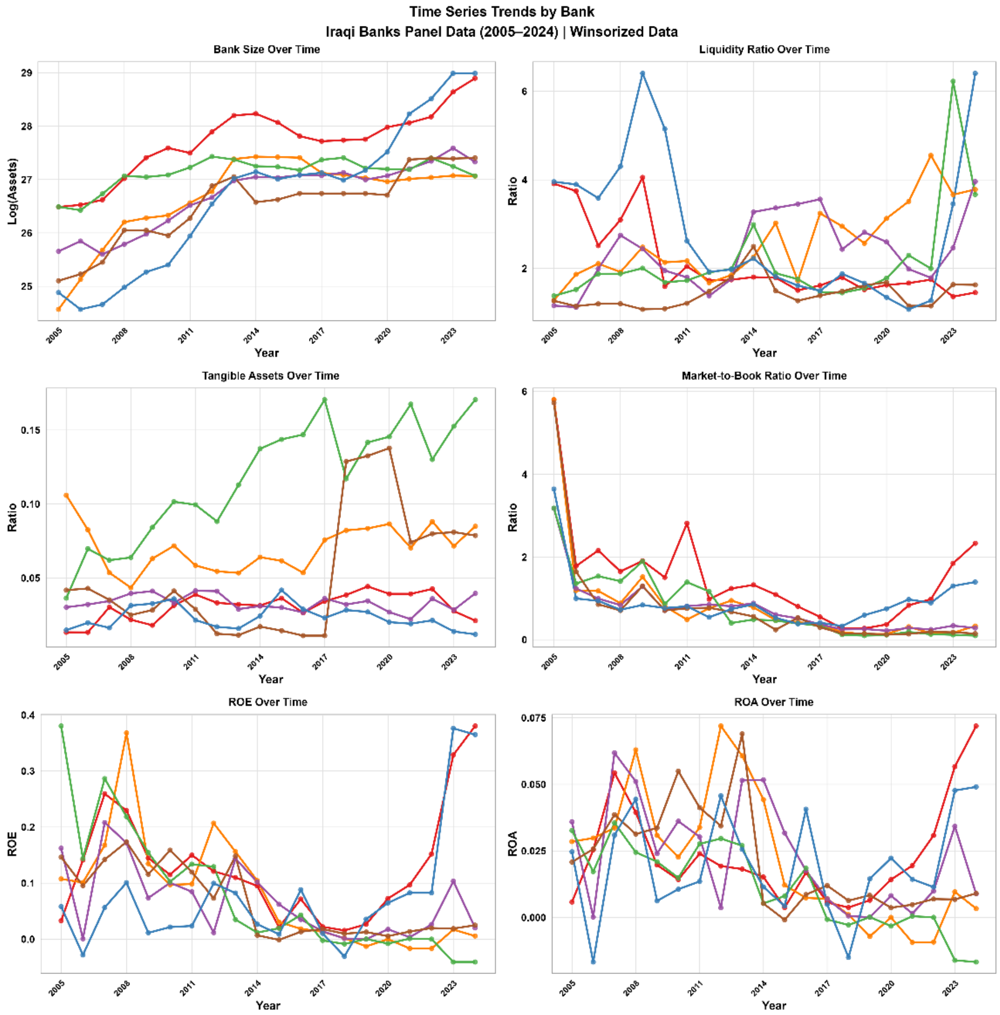
ROE and ROA figures (8.30% and 2.00%, respectively) hide the volatile trend, depicted in Table 1. These performance measures generally rose to a peak around the late 2000s, sharply plummeted in the mid-2010s in response to conflict and economic slowdown and later improved for some banks post-2020 (Figure 3). ROE and ROA show that Iraqi banks experience strong profitability volatility over time rather than stable performance. The rise in the late 2000s, sharp decline in the mid-2010s, and partial recovery after 2020 reflect the influence of political instability, economic shocks, and subsequent stabilization (Saifadin, 2025).



Source: Prepared by researchers using MATLAB software

Figure (3) Bank-wise trends in banking performance indicators (ROE and ROA) across Iraqi commercial banks

The plot of BankSize versus the market - to - book ratio, presented in Figure 4, shows monotonically growing bank size but low market - to - book ratios from 2007 onward until a partial recovery, the market - to - book behavior of Iraqi banks resembles that of banks in other developing markets that experienced similar pressures (Mhlongo et al., 2025; Yamin et al., 2025).



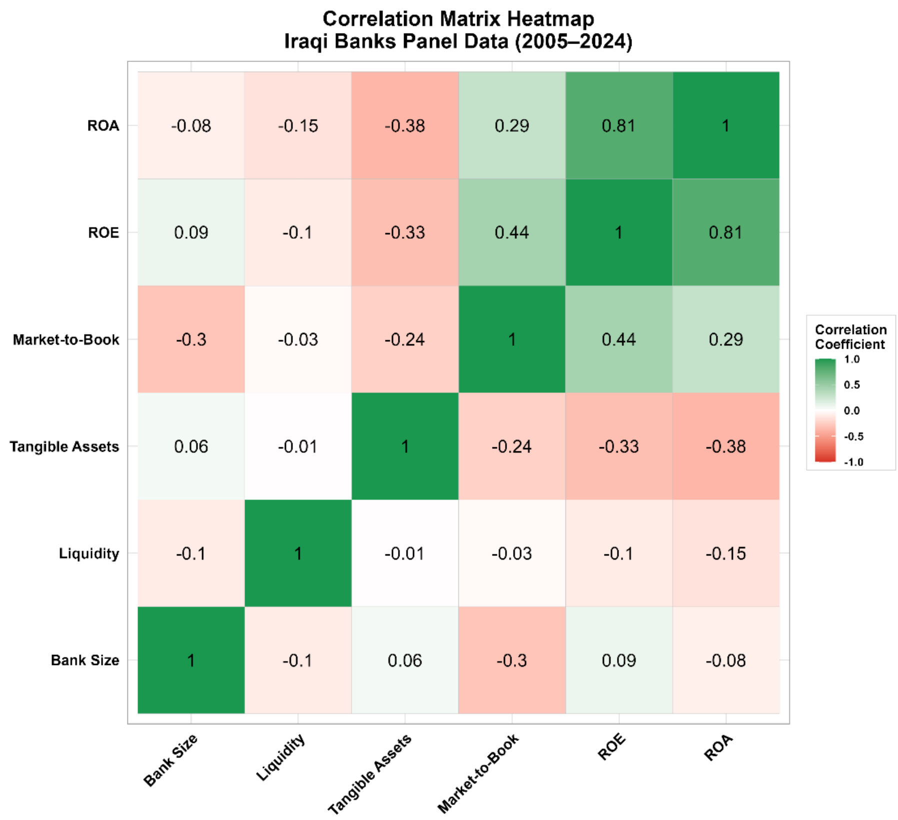
Source: Prepared by researchers using MATLAB software

Figure (4) Time-series trends of capital structure and banking performance variables across Iraqi commercial banks

4.2 Correlations analysis

The correlation matrix heatmap shows a strong correlation between ROE and ROA (r = 0.81), even though these variables reflect different profitability aspects (Figure 5). This strong relationship signifies that the profitability of the sampled banks is driven by common factors, irrespective of the specific performance metric chosen (Monea, 2016). Among the independent variables, the market - to - book ratio has the highest correlation with both ROE (r = 0.44) and ROA (r = 0.29). This finding aligns with the market timing theory, indicating that banks with higher market valuations have better financial performance. Tangible assets are negatively correlated with both ROE (r = −0.33) and ROA (r = −0.38). This indicates that the possession of substantial, illiquid assets is detrimental to a bank's profitability compared to flexibility and financial intermediation. Liquidity has a weak negative correlation with both ROE (r = −0.10) and ROA (r = −0.15). This result might imply that over - liquidity makes banks excessively conservative, sacrificing potential returns for safety (Jahanzeb, 2013). Bank size exhibits a low and insignificant correlation with both ROE (r = 0.09) and ROA (r = −0.08), contradicting the common hypothesis that larger firms generally enjoy better performance (Albahadly & Al-

Hashemi, 2023). The low correlation among the predictor variables indicates that multicollinearity is unlikely to be a significant issue in regression analysis.



Source: Prepared by researchers using R-STUDIO software

Figure (5) Correlation matrix heatmap of capital structure indicators and banking performance variables

4.3 Diagnostics and model selection

Regression models aren't reliable unless the data checks out. The stationarity tests, using Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS), Moon-Perron (MW), and Hadri, mostly confirm stationarity for BankSize, Liquidity, and Tangible Assets. The panel unit root results indicate that BankSize, Liquidity, and Tangible Assets are largely stationary across most tests, with strong significance in LLC ($P = 0.001$, 0.022, 0.032) and MW ($P = 0.001$, 0.025, 0.012), supporting their use in regression analysis. In contrast, the Market-to-Book ratio shows non-stationarity in LLC ($P = 1.000$) and IPS ($P = 0.210$), while ROE and ROA also display mixed stationarity results (e.g., ROA MW $P = 0.005$ but IPS $P = 0.088$) (Table 2). The unit root tests suggest that most core explanatory variables (bank size, liquidity, and tangible assets) are stationary, indicating stable statistical properties suitable for panel regression analysis. However, the mixed results for the market-to-book ratio and profitability measures imply some underlying variability, likely reflecting structural changes and macroeconomic shocks in the banking environment (O'Connell, 2023).

Table (2) Panel unit root test results for capital structure indicators and banking performance variables (LLC, IPS, MW, and Hadri tests)

Variable	LLC stat	LLC *P* value	IPS stat	IPS *P* value	MW stat	MW *P* value	Hadri stat	Hadri *P* value
Bank size_W	-2.983	0.001	-2.172	0.015	32.873	0.001	21.532	0.000
Liquidity_W	-2.016	0.022	-1.229	0.110	23.387	0.025	9.798	0.000
Tangible assets_W	-1.856	0.032	-2.155	0.016	25.548	0.012	8.656	0.000
Market to book_W	6.336	1.000	-0.806	0.210	13.874	0.309	11.502	0.000
ROE_W	0.440	0.670`	0.548	0.708	6.871	0.866	13.407	0.000
ROA_W	-0.930	0.176	-1.355	0.088	28.242	0.005	10.073	0.000

LLC stat=Levin–Lin–Chu statistic; IPS stat= Im–Pesaran–Shin statistic; MW stat= Maddala–Wu statistic; Hadri stat= Hadri Statistic; ROE = return on equity; ROA = return on assets; W = Within-transformed variable (demeaned panel series used in estimation); source: prepared by researchers.
Source: Prepared by researchers.

The performance variable results meet three tests that reveal weaknesses: heteroskedasticity issues in ROE=25.574 and ROA=10.356. Serial correlation appears on both models (ROE=40.769, ROA=37.405) (Table 3). Performance metrics give varied results - either one or neither set of tests on ROE produces similar test statistics (hence caution is recommended in interpretation). We use the Kao - type cointegration tests to address possible doubts over test results. Here, the stats on ROE and ROA are similar and statistically significant (Kao, 1999; Metwally et al., 2025; Pedroni, 2004). Finally, cross - sectional dependence issues appear on ROE (Pesaran CD = 4.858) and ROA (Pesaran CD = 4.386). These are typical problems and require robust corrections than abandonment of models.

Table (3) Diagnostic test results for heteroskedasticity, serial correlation, cointegration, and cross-sectional dependence in ROE and ROA models

Diagnostic	Model	Statistic	*P* value
Heteroskedasticity tests (Breusch-Pagan)	ROE	25.574 (df=4)	0.000
	ROA	10.356 (df=4)	0.035
Serial correlation tests (Breusch-Godfrey/Wooldridge)	ROE	40.769 (df=20)	0.004
	ROA	37.405 (df=20)	0.010
Cointegration tests (Kao-type ADF on residuals)	ROE	-5.467	0.010
	ROA	-6.591	0.010
Cross-sectional dependence tests (Pesaran CD)	ROE	4.858	0.000
	ROA	4.386	0.000

Source: prepared by researchers

In addition, multicollinearity tests shown in Table 4 are fine: all variables are less than the threshold value of 10 (Bank size = 1.117, Liquidity = 1.015, Tangible assets = 1.064, Market to book = 1.172). The VIF remains low for each variable, making sure each predictor stands alone and that the coefficients are reliably stable (O'brien, 2007).

Table (4) Variance Inflation Factor (VIF) results for multicollinearity diagnostics of independent variables

Variable	VIF	Tolerance
Bank size_W	1.117	0.895
Liquidity_W	1.015	0.985
Tangible assets_W	1.064	0.940
Market to book_W	1.172	0.853

Source: prepared by researchers

Table 5 illustrates Hausman test results on deciding panel specifications. About ROE, the Hausman test statistic ($\chi2 = 17.040$, $P = 0.002$) reject random effects (henceforth we rely on the fixed effects method because ROE strongly relies on timing decisions on issuing equity shares), while random effects can be used for the ROA model (Baltagi, 2021; Hausman, 1978).

Table (5) Panel data estimation and model selection results for ROE and ROA using Hausman, F-test, and Breusch–Pagan LM tests

Hausman test (FE vs RE)	**Chi_Sq**	**df**	***P* value**	**Preferred model**
ROE	17.040	4	0.002	Fixed effects
ROA	3.512	4	0.476	Random effects
F-test (pooled OLS vs FE)	**F_Stat**	**df**	***P* value**	**Preferred model**
ROE	3.185	5,110	0.010	Fixed effects
ROA	1.268	5,110	0.283	Pooled OLS
BP LM test (pooled OLS vs RE)	**Chi_Sq**	**df**	***P* value**	**Preferred model**
ROE	0.009	1	0.922	Pooled OLS
ROA	0.397	1	0.529	Pooled OLS

FE = fixed effects; RE = random effects; OLS = ordinary least squares; BP LM test = Breusch–Pagan Lagrange multiplier test; Chi_Sq (χ^2) = Chi-square statistic; F-test (F_Stat) = F-statistic test; df = degrees of freedom; source: prepared by researchers

4.4 Panel data analysis

Two models were thus considered to capture panel data for performance variables: fixed effects regression for ROE (Table 6) and Pooled OLS for ROA (Table 7). The two regression models are empirical explanations about market timing signals and banks' performances of listed Iraqi commercial banks. Through utilizing the fixed effect model, researchers aim to control for unobserved, time - invariant characteristics of banks, focusing instead on observed variation within banks over time and, therefore, better explaining variations in ROE. Due to the presence of heteroskedasticity and autocorrelation confirmed by Table 3, this work adopts robust standard errors (cluster robust standard errors). Among the four predictors in both equations, Tangible Assets has the strongest and most statistically significant effect. A negative coefficient of −1.489 is estimated for ROE with $P = 0.008$. For each unit increase in tangible assets (as % of total assets), there's approximately 1.5% reduction in ROE, which outweighs the effect of all other variables, as clearly depicted in Figure 5. This aligns with previous theory, suggesting that investments made in property, plant and equipment don't generate banking income, such as net interest income, net non - interest income, fees or mediation activities

(Berger & Bouwman, 2013). Market - to - Book ratio, instead, has a significant positive effect on ROE: the estimated coefficient is 0.036 with *P* < 0.001, indicating that the more a bank is overvalued in the stock market, the higher its ROE performance, providing strong support for the Baker & Wurgler (2002) hypothesis in this panel data context. The Bank Size has a slightly positive but statistically not significant effect (β = 0.024, *P* = 0.229) on ROE, whereas the Liquidity variable seems to have a negligible effect (β = −0.003, *P* = 0.826) (Table 6). The model R - squared statistic is 36%, which is generally acceptable in behavioral finance studies given that behavior of managers/boards could affect the market - timing signals used here (Baltagi, 2021).

Table (6) Fixed effects regression results for Return on Equity (ROE) in relation to market timing-based capital structure indicators in Iraqi commercial banks

ROE: fixed-model	Variable	Estimate	Std error	Statistic	*P* value
Standard model	Bank size_W	0.024	0.010	2.413	0.017
	Liquidity_W	-0.003	0.007	-0.469	0.640
	Tangible assets_W	-1.489	0.297	-5.007	0.000
	Market To book_W	0.036	0.008	4.348	0.000
Cluster-Robust SE (HC1)	Bank size_W	0.024	0.020	1.210	0.229
	Liquidity_W	-0.003	0.015	-0.221	0.826
	Tangible assets_W	-1.489	0.550	-2.707	0.008
	Market to book_W	0.036	0.009	4.118	0.000
R_squared = 36%					

ROE = return on equity; source: prepared by researchers

When we switch to the ROA model, we apply a pooled OLS regression combining both cross - sectional variation and time series. Similar to the ROE model, we observe that a higher ratio of tangible assets to total assets results in a significant negative impact on ROA (β = −0.163, *P* < 0.001), whereas the market - to - book ratio has a significant positive impact on ROA (β = 0.004, *P* = 0.001). However, these coefficients have much smaller absolute values compared to those of the ROE model. This is because total assets are much larger than equity, hence the larger denominator. The variables size and liquidity aren't significant predictors (*P* = 0.913 for size, *P* = 0.143 for liquidity), implying no significant benefits in scale or liquidity in these circumstances. The adjusted R - squared for this model is 21%, down from 25% for the ROE model (Table 7). We expect the asset - based performance variable to have less explanatory power, as indicated by (Wooldridge, 2010). Unlike the fixed - effects model in the previous step, the pooled OLS model estimates a single intercept (0.037) that applies to all banks and years, treating the pooled cross - sectional times series as a single entity. The Hausman test and the BP LM test in Table 7 confirm the pooled OLS model over the fixed - effects one.

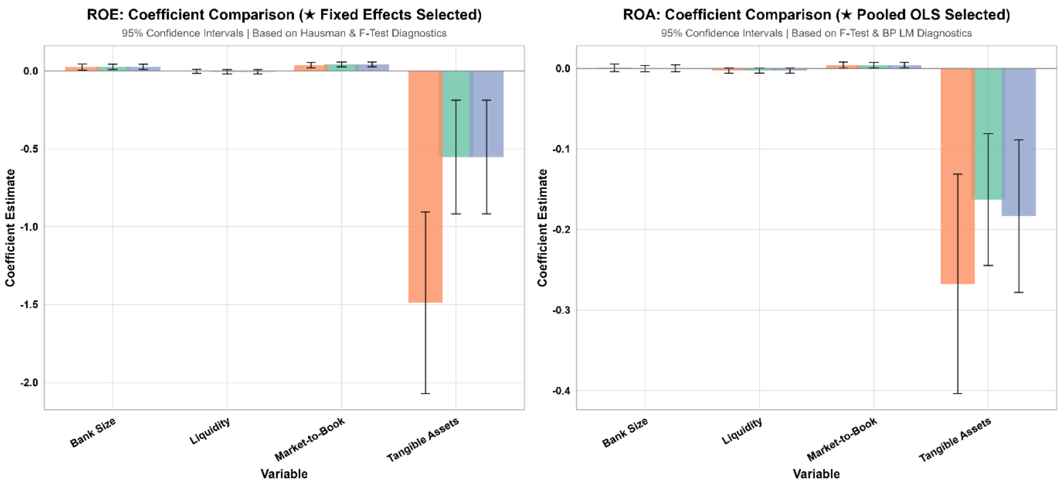
Table (7) Pooled ordinary least squares regression results for Return on Assets (ROA) with Heteroskedasticity-Consistent (HC1) robust standard errors based on market timing indicators (bank size, liquidity, tangible assets, and market-to-book ratio)

ROA: Pooled-Model	Variable	Estimate	Std. error	Statistic	*P* value
Standard model	(Intercept)	0.037	0.054	0.692	0.490
	Bank size_W	0.000	0.002	-0.109	0.913

	Liquidity_W	-0.003	0.002	-1.817	0.072
	Tangible assets_W	-0.163	0.042	-3.891	0.000
	Market to book_W	0.004	0.002	2.287	0.024
HC-Robust SE (HC1)	(Intercept)	0.037	0.058	0.636	0.526
	Bank size_W	0.000	0.002	-0.110	0.913
	Liquidity_W	-0.003	0.002	-1.475	0.143
	Tangible assets_W	-0.163	0.017	-9.360	0.000
	Market to book_W	0.004	0.001	3.338	0.001
R_squared = 21%					

ROA = return on assets; OLS = ordinary least squares regression; HC1 = heteroskedasticity-consistent type 1 robust standard errors source: prepared by researchers

Looking at the plots in Figure 6 for the pooled OLS model, the confidence intervals for tangible assets are entirely negative and don't span zero for either ROE or ROA, while the confidence interval for the market - to - book ratio for both ROE and ROA lies entirely above zero. These graphical results are consistent with our findings.



Source: Prepared by researchers using R-STUDIO software

Figure (6) Regression coefficients for Return on Equity (ROE) and Return on Assets (ROA) models with Heteroskedasticity-Consistent (HC1) robust standard errors across market timing-based capital structure variables

Let $\hat{\alpha}_i$denotes the bank - specific intercept recovered for each bank, which is the constant value subtracted from each observation for a particular bank, which will sweep away time - invariant unobserved heterogeneity. The bank intercepts play crucial role on Table 8. Baghdad Bank value is −0.549. The other intercepts values are in range [−0.430, −0.563]. These bank - specific negative values for all 6 banks confirm that this banking sector performed poorly compared to overall average in Iraq, especially as Iraqi banking was relatively low - return over the major portion of this sample period. The fixed - effects intercepts for the ROE equation are negative (all banks score below the average estimate ranging from −0.430 Iraqi Middle East to −0.563 National Bank), while the estimated fixed - effects intercepts for the ROA equation are slightly positive. This means that, after controlling for the market timing factors, banks still manage slightly higher asset returns relative to their individual benchmarks (Cobbinah et al., 2024).

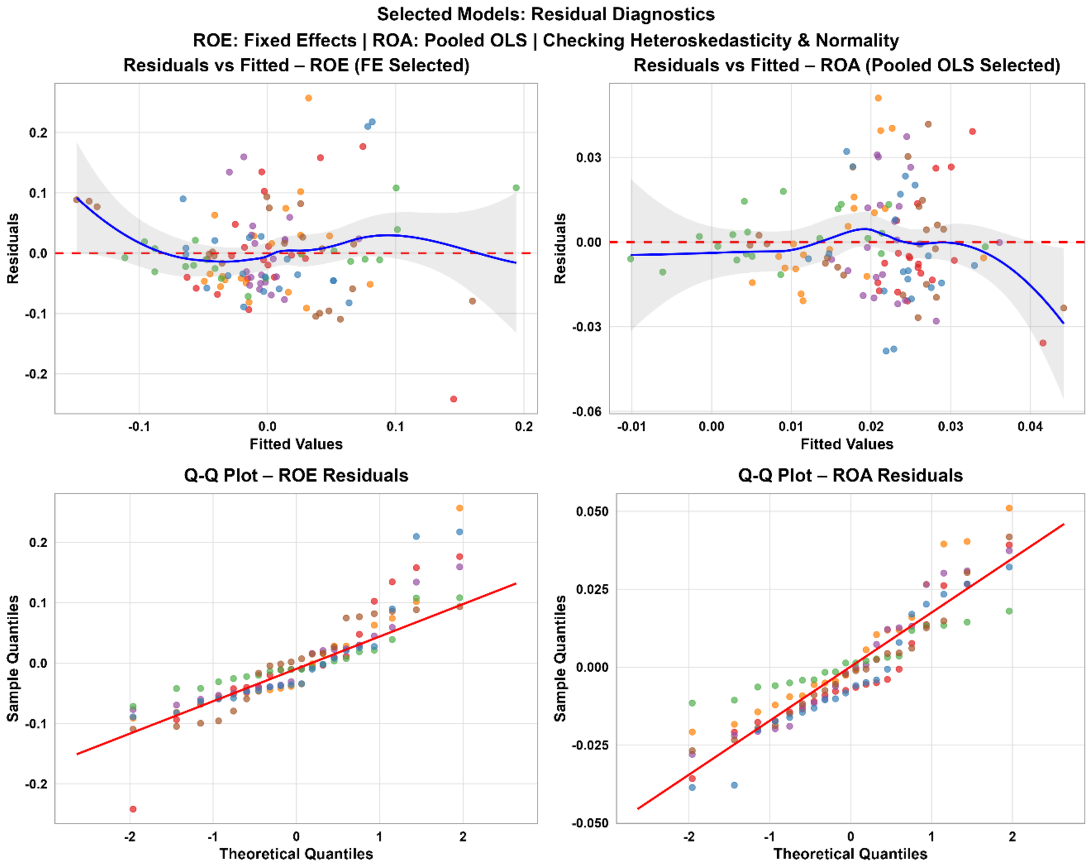
Table (8) Bank-specific fixed effects intercepts from fixed effects regression models for Return on Equity (ROE) and Return on Assets (ROA) in Iraqi commercial banks

Bank	FE_ROE	FE_ROA
Baghdad	-0.549	0.009
Gulf Commercial	-0.488	0.022
Investment Bank	-0.553	0.014
Iraqi Middle East	-0.430	0.023
Mosul	-0.528	0.014
National Bank	-0.563	0.008

FE = fixed effects estimator/model; ROE = return on equity; ROA = return on assets; source: prepared by researchers

Iraqi Middle East Bank has consistently high intercepts in both ROE and ROA compared with other banks, reflecting its high proportion of tangible assets in the balance sheet (Table 1 and Figure 1). Such a structure mitigates but doesn't completely offset its poor performance, according to Hsiao (2014).

The residual versus fitted value plots for both models (Figure 7) reveal no visible patterns or significant systematic curvature along the line. Except for widening of the residuals at the tails, for the ROE model, the plotted lines hover near the zero line, consistent with the heteroskedasticity we identified. The normal Q - Q plots (Figure 7) also confirm the suitability of the coefficient estimates, as the residuals fall close to the line, except for some outliers [as expected given the Iraq war of 2003 and subsequent economic instabilities that marked this period and so forth, per Cameron & Trivedi (2005)].

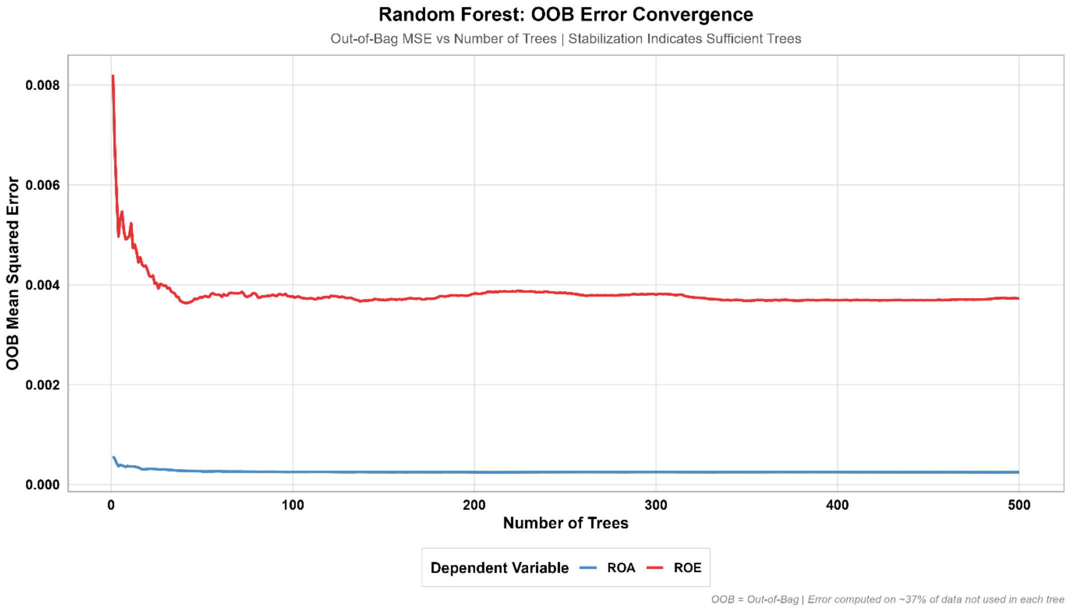


Source: Prepared by researchers using R-STUDIO software

Figure (7) Residual distribution, residual-versus-fitted plots, and normal Q–Q diagnostics for the Return on Equity (ROE) and Return on Assets (ROA) regression models

4.5 Random Forest analysis

To further test our predictions, we employ a nonparametric method in machine learning: the Random Forest regression (Breiman, 2001). This technique generates hundreds of decision trees from different bootstrap samples of the data and uses an ensemble average to predict the outcomes. Machine learning approaches such as Random Forest are advantageous because they can capture higher - order interactions among predictors that may be missed by conventional linear regression models. The Random Forest model is trained using 500 trees. In Figure 8, it's shown that the out - of - bag (OOB) error, which represents the error of prediction for observations that were not included in a particular tree's bootstrap sample, converges quickly to a stable value well before 100 trees are built, which indicates that the forest size is sufficient. Additional trees offer no further meaningful improvement. This behavior itself supports the consistency and reliability of the model and its estimates (Hastie et al., 2009).



Source: Prepared by researchers using R-STUDIO software

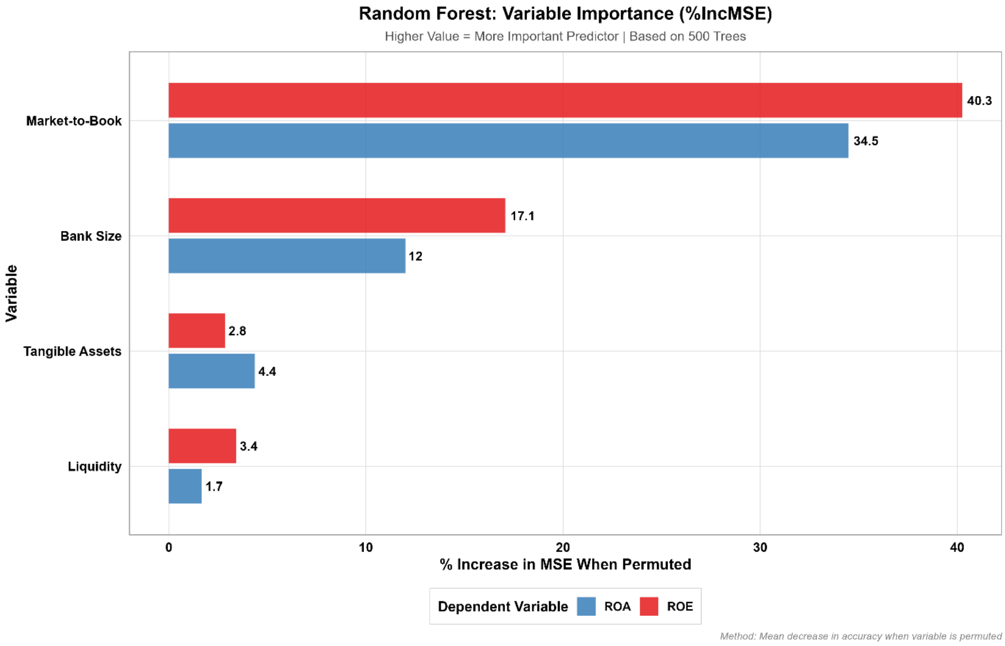
Figure (8) Convergence of Out-of-Bag (OOB) prediction error across 500 Random Forest trees for banking performance models

As for the importance of predictors, according to permutation - based rankings (% increase in Mean Squared Error when a randomly permuted predictor is left out), the order of variables shifts compared with the previous step. While the panel model found tangible assets to be the most significant predictor in the ROE equation (with negative impact), the Random Forest approach finds the market - to - book ratio to be the dominant predictor for both ROE (%IncMSE = 40.253) and ROA (%IncMSE = 34.480), far outweighing bank size (17.069 for ROE, 12.003 for ROA) (Table 9 and Figure 9). This outcome difference shouldn't be seen as contradictory: the impact coefficient in a regression captures direct effects, whereas machine learning methods estimate variables' overall importance in prediction based on combined effects (Tonidandel & LeBreton, 2011).

Table (9) Random Forest variable importance measures for predicting Return on Equity (ROE) and Return on Assets (ROA) using market timing-based capital structure indicators

Model	Variable	IncMSE	Inc Node Purity	Rsquared
ROE	Market to book_W	40.253	0.460	62%
	Bank size_W	17.069	0.299	
	Liquidity_W	3.420	0.095	
	Tangible assets_W	2.849	0.144	
ROA	Market to book_W	34.480	0.019	45%
	Bank size_W	12.003	0.010	
	Tangible assets_W	4.364	0.009	
	Liquidity_W	1.665	0.006	

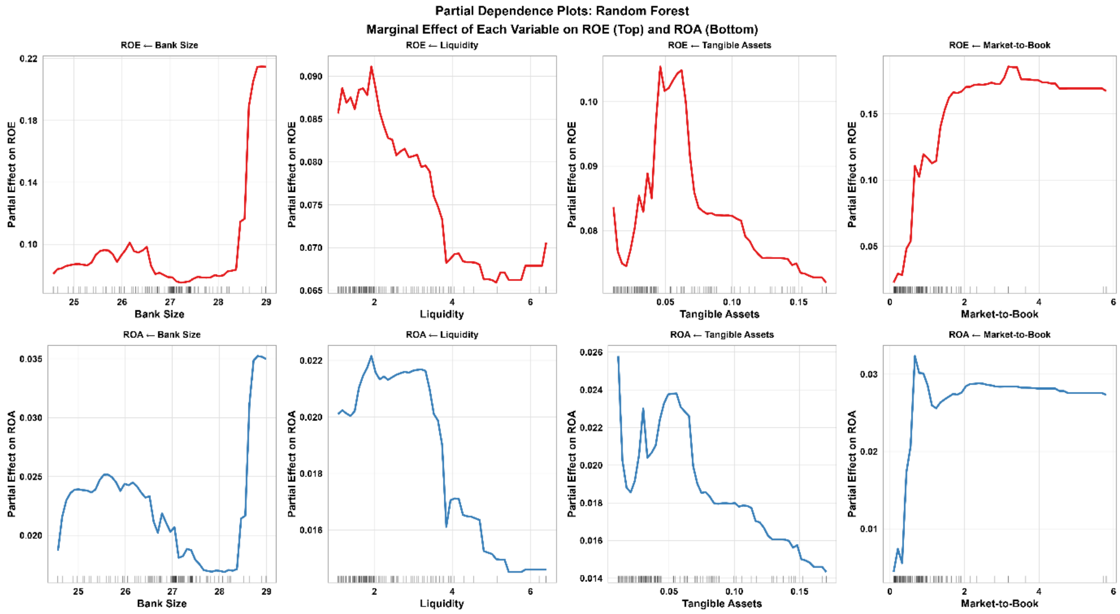
ROE = return on equity; ROA = return on assets; IncMSE = increase in mean squared error after variable permutation; source: prepared by researchers



Source: Prepared by researchers using R-STUDIO software

Figure (9) Feature importance of Random Forest predictors

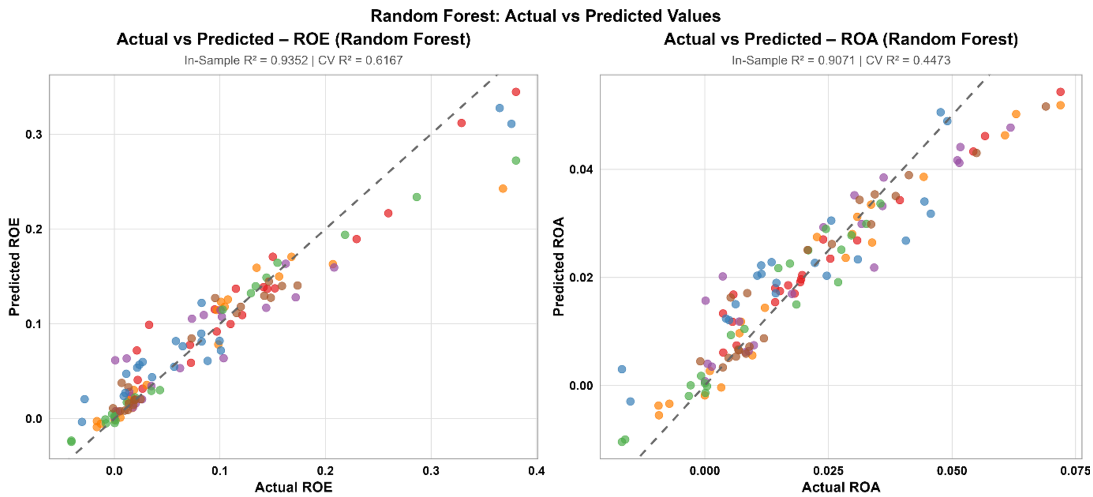
Most striking is the message that the relationship between market - to - book and future performance is nonlinear, it interacts with other variables, a simple, linear coefficient can't model these (Baker & Wurgler, 2002). Intangible assets and liquidity seem far less important than their market - to - book counterparts in these flexible models. While more liquidity has a linear negative impact on ROE, further liquidity leads to less negative ROE - the curve grows steeper as liquidity rises to moderate levels, only to taper off again. Market - to - book grows quickly early on to some value but tapers off quickly thereafter - the benefit to ROE of large market - to - book values isn't linear. ROA patterns display some similar properties, but effects are smaller. In sum, ML together with the classical econometric modeling framework seems necessary and vital (Figure 10). The reality of how banks achieve these objectives doesn't obey simple rules that may be linearly captured in traditional statistical analysis (Zhao & Hastie, 2021).



Source: Prepared by researchers using R-STUDIO software

Figure (10) Partial dependence plots for Return on Equity (ROE) and Return on Assets (ROA)

Figures 11 present observed vs. predicted values of ROE and ROA for a Random Forest model over a set of in - sample and validation values. For the 161 sample banks (03/2008-09/2009), a random forest achieves $R^2 = 0.935$ for ROE and $R^2 = 0.907$ for ROA. In contrast, a typical panel model yields R^2 of 0.360 and 0.211, respectively. The out - of - sample fit is more of a true assessment of learning. Here, cross - validation of that Random Forest model on 50 bootstrap samples produces CV $R^2 = 0.617$ and 0.447 for ROE and ROA, respectively, suggesting that the model has learned generalized features than fitting noise (James et al., 2021).



Source: Prepared by researchers using R-STUDIO software

Figure (11) Observed vs Predicted Performance of Return on Equity (ROE) and Return on Assets (ROA) (Random Forest model)

4.6 Model comparison: Panel vs. Random Forest

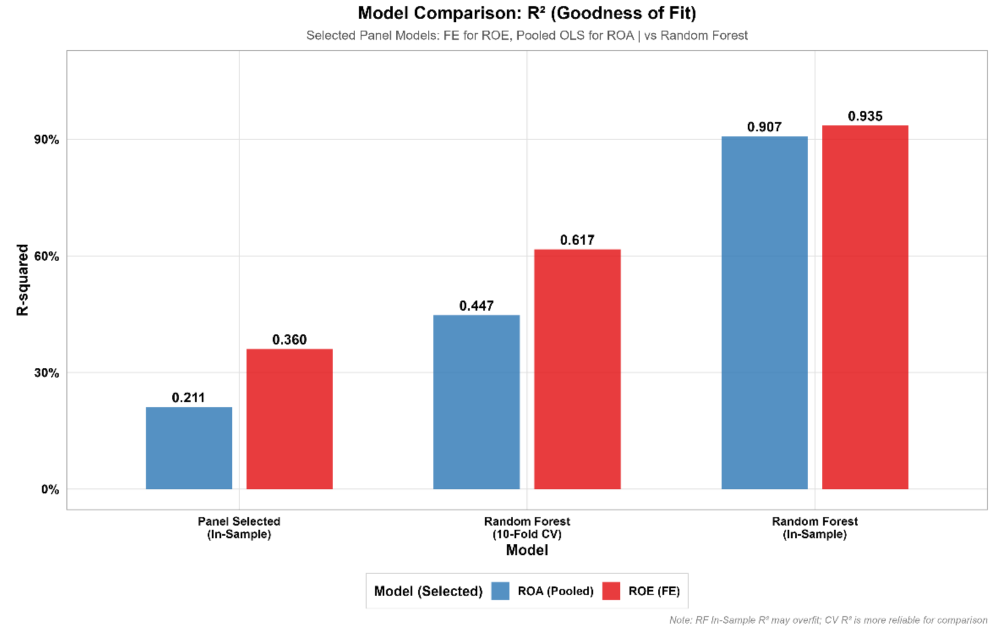
When traditional panel models are contrasted with Random Forest, the results are clearly different. A comparison of performance for each method on the data is insightful. In - sample, the R^2 of Random Forest was 0.935 for ROE and 0.907 for ROA, while for panel models, it was 0.360 and 0.211, respectively (Table 10). When Random Forest was adjusted by penalties derived from cross - validation, these values were lowered but the model still clearly outweighed the panel models in performance. Complex patterns exist in data and there are advantages to be gained in trying to model them more comprehensively.

Table (10) Performance comparison of panel regression models and Random Forest for Return on Equity (ROE) and Return on Assets (ROA) (including error metrics, cross-validation results, and model properties)

Metric	Panel_FE ROE	RF_ROE	Panel pooled ROA	RF_ROA
RMSE (In-sample)	0.1125	0.0273	0.0176	0.0071
MAE (In-sample)	0.088	0.0185	0.0138	0.0053
R^2 (In-sample)	0.3601	0.9352	0.2107	0.9071
RMSE (10-fold CV)	N/A	0.0596	N/A	0.0154
MAE (10-fold CV)	N/A	0.0427	N/A	0.0117
R^2 (10-fold CV)	N/A	0.6167	N/A	0.4473
Interpretability	High	Low (black-box)	High	Low (black-box)
Handles nonlinearity	No	Yes	No	Yes
Handles interactions	Manual only	Automatic	Manual only	Automatic
Requires assumptions	Yes	No	Yes	No
Inference (*P*-values)	Yes	No	Yes	No

RMSE=root mean squared error; MAE= mean absolute error; ROE = return on equity; ROA = return on assets; N/A= not applicable; CV= cross-validation; FE = fixed effects estimator/model; source: prepared by researchers

RMSE shows another angle of this story (Figure 12). In our panel fixed effects model on ROE, the RMSE is 0.1125 versus 0.0273 and 0.0596 for the respective in - sample and cross - validated Random Forests - so Random Forests perform much better. With ROA, Random Forests perform better yet, but only by a small amount. It turns out that market timing signals contain rich patterns that are nonlinear and are important for predicting banking outcomes (Mullainathan & Spiess, 2017).



Source: Prepared by researchers using R-STUDIO software

Figure (12) Comparison of root mean squared error (Goodness of fit) and predictive performance between panel fixed effects model and Random Forest for Return on Equity (ROE) and Return on Assets (ROA)

Both techniques agree on the main variables. Panel standardized coefficients, as well as the Variable Importance plot of the Random Forest model, rank market - to - book and tangible assets as the most important predictor variables (Figure 13). What differs is the relative ranking. Panels place much more weight on the negative effect of tangible assets, whereas Random Forests give more importance to market - to - book due to its nonlinear, spread - out impact. Liquidity plays a consistently minor role in both models, being ranked as the least important predictor variable for both panels (Breiman, 2001).

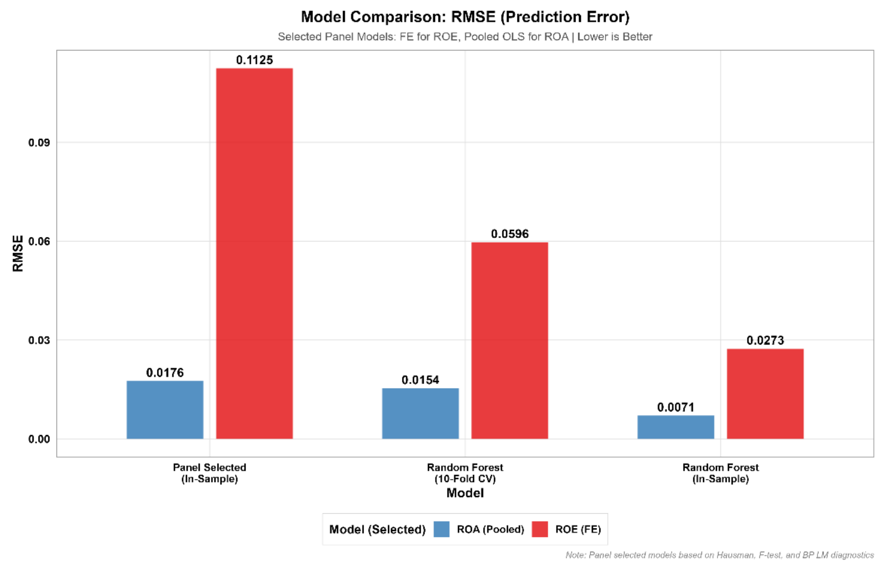
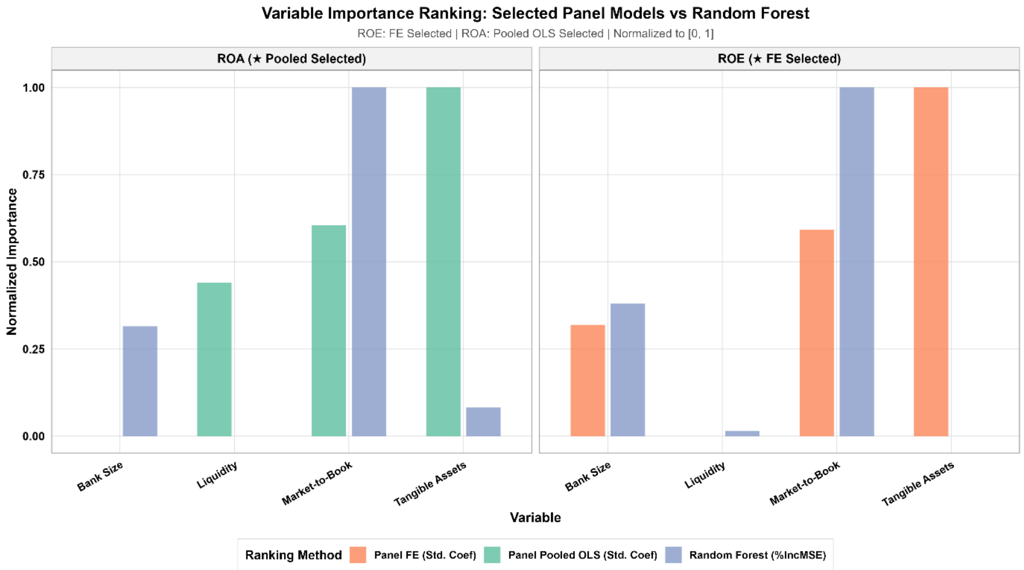


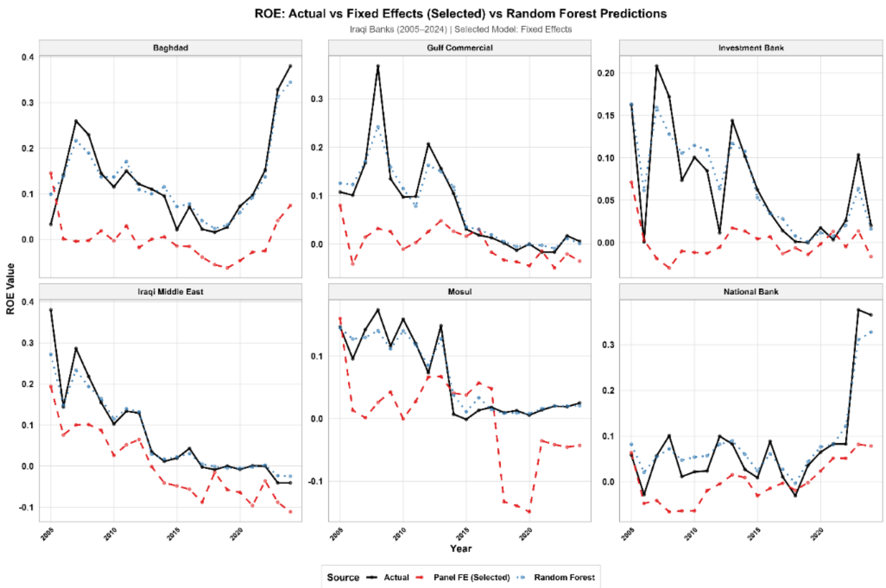
Figure (13) Comparison of variable importance rankings (mean squared error) between panel regression and Random Forest models for Return on Equity (ROE) and Return on Assets (ROA)

Finally, Figure 14 and Figure 15 shows a time - series plot where the predictions (blue dots) of the Random Forest are close to actual bank outcomes, compared to the panel model where the estimations tend to lag behind strong upturns, downplay peaks and can't catch the depth of downturns - especially around the periods that included Baghdad and National Bank following 2020.



Source: Prepared by researchers using R-STUDIO software

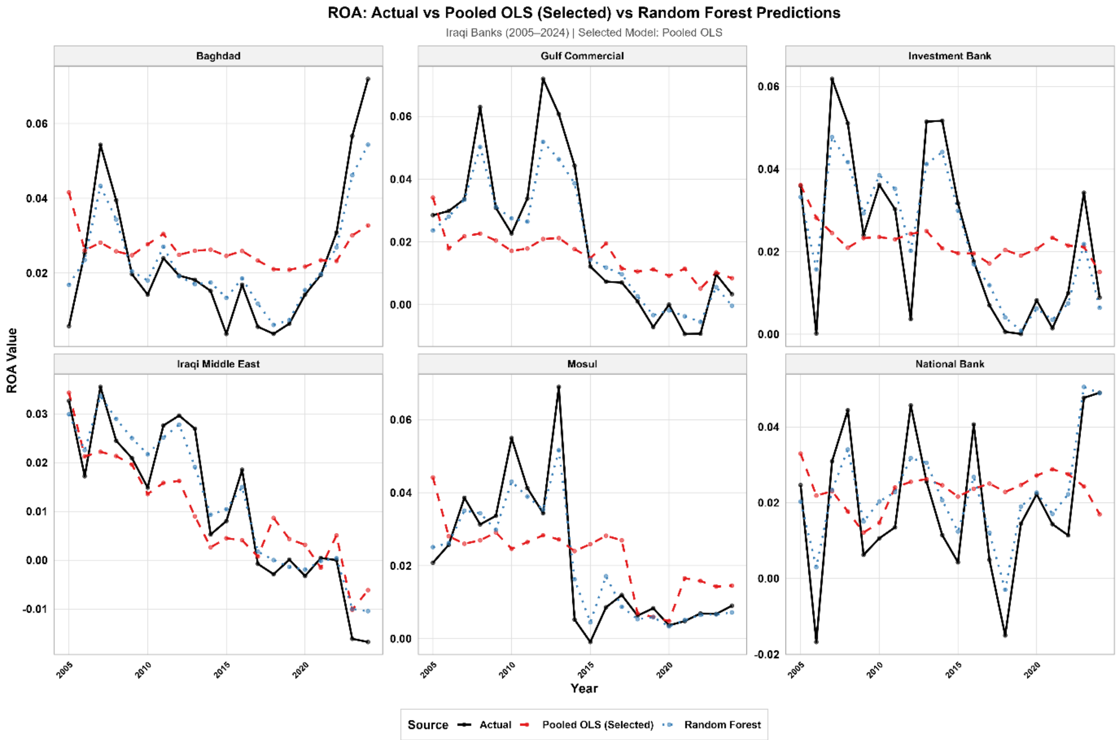
Figure (14) Feature importance ranking comparison between panel regression models for Return on Equity (ROE) and Return on Assets (ROA) and Random Forest models



Source: Prepared by researchers using R-STUDIO software

Figure (15) Comparison of actual, fixed effects, and random forest predictions for Return on Equity (ROE)

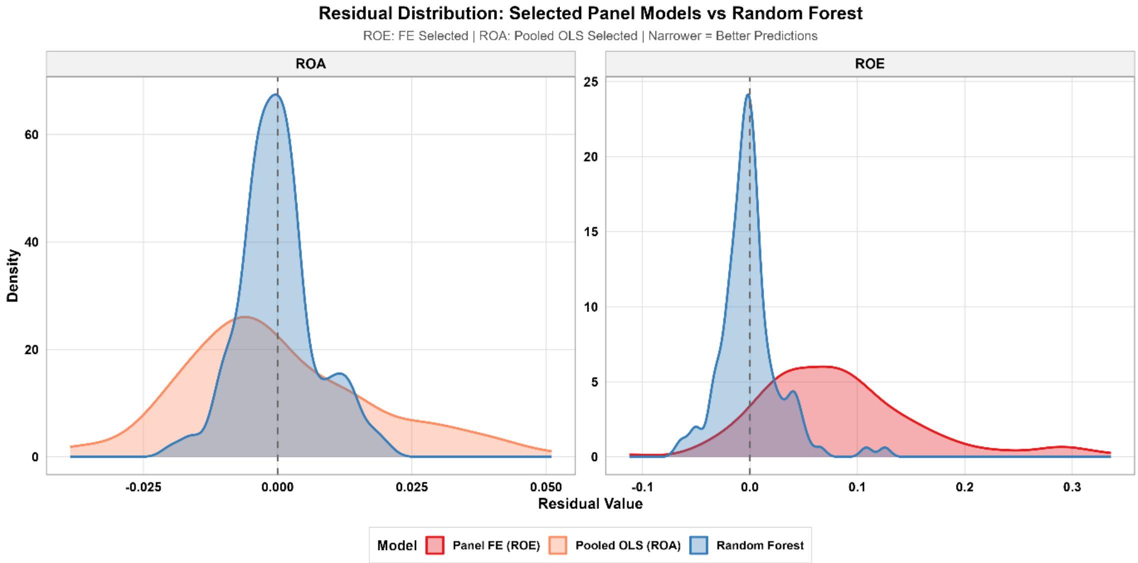
Similarly, Figure 16, showing residual densities from the models for panel fixed effects, reveals that Random Forest residuals are closely concentrated around 0, whereas those from the panel regressions show a fatter distribution toward large and small negative residuals and unusually large positive values (Hastie et al., 2009).



Source: Prepared by researchers using R-STUDIO software

Figure (16) Comparison of prediction residual distributions between panel fixed effects and Random Forest models for Return on Assets (ROA)

This doesn't mean we should prefer an assumption - free black - box Random Forest prediction model over panels, as we believe both tools are useful and necessary. Panel regressions give us the required tools for statistical inference and interpretation (Table 10) that are important in testing theory and in making policy recommendations, with their coefficients reflecting the sign of effects and their statistical significance (p - values), enabling causal interpretation (Mullainathan & Spiess, 2017). Machine learning prediction models such as Random Forests, meanwhile, provide powerful, assumption - free, high - accuracy predictions and an unsurpassed capability to capture nonlinearity (Athey & Imbens, 2019). These models lack interpretability as well as a basis to establish causal relationships, which are instead handled by the panel regression models (Figure 17). We conclude by suggesting that an integrated strategy is best: use traditional methods for inference and theory testing, while embracing machine learning for richer prediction and to help identify blind spots we can't see ourselves (Athey & Imbens, 2019).



Source: Prepared by researchers using R-STUDIO software

Figure (17) Comparison of residual distributions between panel regression models and Random Forest prediction models for Return on Equity (ROE) and Return on Assets (ROA)

5. Conclusions

The researchers sought to find evidence: Does market timing theory lead to significant behavioral market timing choices by Iraqi bankers, affecting the profitability of their respective financial institutions? The study employs two decades of data on six Iraqi financial institutions, resulting in 120 panel observations. From a period starting after the U. S. Intervention in Iraq in 2003, through the sectarian violence between 2005 and 2007, to subsequent reconstruction periods, the empirical analysis demonstrated consistent, positive impacts of managerial market timing activity. The market - to - book value ratio had the most substantial positive impact. As observed in the Random Forest model, this variable registered the highest feature importance (40.3% IncMSE for ROE and 34.5% IncMSE for ROA) and robust positive relationships were also detected in the panel regression analyses ($\beta = 0.036$ for ROE, $\beta = 0.004$ for ROA). Both methodologies' concordance suggests that banks enjoying favorable market valuations likely have better investment capital decisions either due to bankers taking advantage of attractive financing windows in the market or simply because market optimism encourages higher returns. Conversely, tangible assets consistently decreased bank performance ($\beta = -1.489$ for ROE fixed effects, $\beta = -163$ for pooled ROA). The tangible nature of physical capital may not translate into profits as well as other assets in a sector whose earnings are mainly derived from financial transactions, than physical ownership. When market - to - book value and tangibility were included in the analysis, bank size and liquidity didn't produce additional informative results. Methodologically, the results reinforce the value of traditional panel models such as fixed - effects regression for ROE and pooled OLS regression for ROA, because of their transparent interpretation and statistical rigor when theory - testing. Random Forest is also valuable in illuminating phenomena that are concealed or smoothed out by standard linear models- such as discrete threshold levels of bank size, diminished positive effects from further market capitalization appreciation and various interaction

patterns that become obscured or flattened by linearity. It's noteworthy that the cross - validated R squared values doubled for both ROE (from 0.36 to 0.62) and ROA (from 0.21 to 0.45) when applying the Random Forest model. Future studies should explore more advanced methods and data that'll reveal deeper underlying structures. The implications of the results indicate that managers should aim to manage bank market valuations more effectively by judiciously entering the market when values are low and exiting when valuations are high, according to the precepts of market timing theory and banks may benefit from optimizing the proportion of tangible assets within their asset structures to improve operational efficiency and profitability.
While this study's findings convincingly link shifts in capital structure - viewed through the lens of market timing theory - to banking performance, several constraints emerged, paving the way for subsequent investigations. The pool was limited to six commercial banks, all listed on the Iraq Stock Exchange, spanning two decades of clean, continuous data (2005–2024). While this focus ensures reliability, it also narrows generalizability—covering Iraq's core sector, but not its entirety, due to chronic data scarcity. Internal, bank-level indicators (size, liquidity, and tangibility) formed the primary independent variables. The study did not incorporate key macroeconomic shocks (such as inflation, interest rates, or economic growth), which likely play major roles in Iraq's volatile setting but remain outside this model's scope. Iraq's banking sector exists in a uniquely turbulent environment (frequent exchange rate shifts, high cash usage, and market instability). Insights from this context may not hold for more stable or developed markets. While the Random Forest algorithm excelled in predictive tasks, its black-box nature means it doesn't supply the inferential clarity (p-values, causal direction) provided by traditional regressions.

In light of these limitations, several paths forward are recommended, including future work could include a broader sample of banks, or benchmark Iraqi banks against others across the MENA region, to test how far these findings extend and to see if market timing dynamics play out similarly elsewhere. Incorporate more macroeconomic variables in the modeling. Future panels or machine learning efforts should explicitly account for economic shocks and broad market trends, isolating the distinct effects of market timing decisions from the broader backdrop of volatility. By combining advanced machine learning algorithms with interpretation tools like SHAP values, researchers can leverage interpretable artificial intelligence to give decision-makers a much more detailed and transparent view of how variables interact in complex, nonlinear ways. This approach doesn't just spit out predictions—it actually helps people understand the reasoning behind those predictions. When leaders see clearly how certain factors drive outcomes, they can make choices with confidence, knowing they're guided by insights they can trust and explain to others. This deeper understanding opens the door to more effective strategies and better risk management, especially in environments where the relationships between variables aren't obvious or straightforward. Another promising direction is applying the framework of market timing theory to other sectors in Iraq, not just banking. Sectors like industry and insurance present unique dynamics, and examining them can reveal whether market valuations have the same effect on performance efficiency as observed in the banking sector. By expanding the analysis beyond banking, researchers can test the robustness of market timing theory and discover how sector-specific factors shape the relationship between market values and operational efficiency. This broader perspective gives policy-makers and business leaders a stronger foundation for adapting strategies across different parts of the economy.

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