“Determinants of banking efficiency in the MENA region: A two-stage DEA-Tobit approach”

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DETERMINANTS OF BANKING EFFICIENCY IN THE MENA REGION: A TWO-STAGE DEA-TOBIT APPROACH

Abstract

In today's volatile financial environment, banks encounter various risks, including political instability, regulatory changes, and global market fluctuations, which can undermine efficiency and threaten systemic stability. This study focuses on banking efficiency in the MENA region, highlighting its crucial role in economic growth and financial stability. This paper addresses the gap in banking efficiency research in the MENA region by evaluating the technical and pure technical efficiency of 59 conventional banks from 11 MENA countries between 2019 and 2023 and identifying the internal and external factors affecting their efficiency. Using a Data Envelopment Analysis, the study evaluates efficiency based on three inputs and two outputs. A panel Tobit regression model is then applied to analyze the impact of eight internal factors and four external factors on efficiency. The findings indicate that just 16% of the MENA banks were technically efficient, with Qatari banks outperforming and banks in Morocco and Jordan underperforming. The Tobit regression model results indicate that both return on assets and capital adequacy positively influence technical efficiency (TE) and pure technical efficiency (PTE). In contrast, Liquidity and operational costs negatively affect PTE and TE. Non-performing loans negatively impact TE but not PTE, and macroeconomic factors positively influence both TE and PTE. In conclusion, banks in the MENA region must prioritize improving their efficiency to stay competitive. The findings offer valuable insights into operational best practices and provide practical guidance for policymakers, regulators, and banking institutions to enhance the performance of the region's financial systems.

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INTRODUCTION

The banking sector is a cornerstone of modern economies, facilitating the flow of capital between savers and borrowers, which stimulates economic activity and promotes growth. However, in today's volatile financial environment, banks face a wide range of risks, including credit, liquidity, and operational risks, as well as external shocks from political instability, regulatory changes, and fluctuations in global markets. These risks can compromise bank efficiency and threaten systemic stability, emphasizing the need to understand how banks operate under varying economic conditions.

Banking efficiency is not just a theoretical concept but a practical measure of how well banks use their resources to generate profits, manage risks, and support economic development. For policymakers and regulators, monitoring banking efficiency is crucial, as inefficiencies can lead to systemic vulnerabilities with broader macroeconomic implications. For banks, enhancing efficiency is crucial for maintaining competitiveness, particularly in regions where financial markets are evolving and becoming more integrated with global markets.

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Despite the recognized importance of banking efficiency, particularly in the Middle East and North Africa (MENA), research on this topic remains limited. The MENA banking sector faces unique challenges, including heightened competition, regulatory changes, and the pressures of globalization, complicating the analysis of its efficiency. The region's diverse economic landscape – ranging from the oil-dependent Gulf Cooperation Council countries to other Arab economies – further underscores the need for a deeper understanding of the factors driving bank efficiency. Most banks in the region, established primarily in the 1970s, are relatively young and still evolving, making the study of their efficiency particularly relevant.

1. LITERATURE REVIEW

Researchers have employed a variety of methodologies to measure bank efficiency, focusing on both technical and allocative aspects, while also identifying key determinants that impact efficiency. The literature on banking efficiency reveals a broad spectrum of findings across different regions and banking systems. Isik et al. (2002) analyzed Turkish banks from 1988 to 1996, identifying inefficiencies primarily due to poor scale management rather than allocative inefficiency. Their study linked inefficiency to the oligopolistic market structure and suggested that reforms could improve competition and managerial performance. Isik et al. (2003) further explored Turkish banking performance, demonstrating that independent bank characteristics, such as ownership and size, significantly correlated with efficiency.

Meanwhile, Catalbaş and Atan (2005) focused on Turkish commercial banks from 2002 to 2004, using DEA and Tobit regressions. They found that capital structure played a crucial role in influencing efficiency. Pasiouras (2008) provided complementary findings by examining Greek banks from 2000 to 2004, highlighting that higher capitalization and loan activity improved efficiency, while ATM adoption had no significant effect.

The analysis of banking efficiency in the MENA region by Naceur et al. (2009) revealed that well-capitalized banks and stronger legal frameworks contributed to efficiency in Moroccan and Tunisian banks. However, high banking concentration was found to diminish efficiency, emphasizing the need for more competitive structures. Similarly, Sufian and Noor (2009) compared Islamic banking sectors in MENA and Asia, reporting that MENA banks were more efficient. Factors such as loan intensity, size, and profitability were found to enhance efficiency.

Shifting focus to Southeast Asia, Abd Karim et al. (2010) analyzed Malaysian and Singaporean banks and supported the "bad management" hypothesis, as non-performing loans were found to negatively impact efficiency. In Jordan, Ajlouni et al. (2011) identified that larger banks were more efficient, although higher capitalization ratios reduced overall efficiency.

In the context of Latin America, Garza-Garcia (2012) explored Mexican banks from 2001 to 2009, finding that inefficiencies were predominantly due to poor technical and scale management. Notably, foreign ownership and loan intensity were found to improve efficiency. In Malaysia, Ismail et al. (2013) contrasted Islamic and conventional banks, revealing that size and capitalization improved efficiency, while loan quality had an adverse effect.

Turning to South Asia, Jha et al. (2013) examined Nepalese banks from 2005 to 2010, where inefficiencies were primarily attributed to technical issues. Private sector and joint venture banks outperformed public sector banks in terms of efficiency. In Libya, Alrafadi et al. (2014) assessed 17 banks from 2004 to 2010, finding that specialized banks exhibited higher cost efficiency. Additionally, efficiency was positively linked to return on investment, risk, and size of operations.

Further research in Indonesia by Havidz and Setiawan (2015) found that factors such as return on assets, operational efficiency, and inflation significantly influenced the efficiency of Islamic banks from 2008 to 2014, supporting the "bad management" hypothesis. Lutfiana and Yulianto (2015) also studied Islamic banks in Indonesia, concluding that the capital adequacy ratio positively impacted efficiency, while operational costs negatively affected it.

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Eldomiaty et al. (2015) examined Egyptian banks from 2001 to 2008 and observed that competition played a crucial role in enhancing efficiency. In Ghana, Adusei (2016) reported that profitability improved efficiency among rural banks, while size and funding quality had a negative effect. Meanwhile, Pambuko (2016) evaluated Islamic banks in Indonesia, finding that smaller banks were generally more efficient.

In Ethiopia, Tesfaye (2016) found that deposits and liquidity positively correlated with efficiency among commercial banks. More recently, Riani and Maulani (2021) assessed Indonesian banks and highlighted the significance of operational cost/revenue and return on equity as determinants of efficiency, while capital adequacy had no impact. Patra et al. (2022) contrasted efficiency in Indian banks, revealing that public sector banks were more efficient and mergers contributed to improved efficiency.

Finally, Istaiteyeh et al. (2024) provided recent insights into Jordanian banks, finding Islamic banks to be more efficient than conventional ones. Return on assets, return on equity, and GDP growth were significantly linked to efficiency, while credit risk and size were not found to be significant factors.

Internal factors, such as funding costs, administrative expenses, and bank size, are consistently found to influence efficiency in empirical research. For example, Nisar et al. (2018) highlighted that funding costs and administrative expenses negatively affect bank efficiency, while advancing loans, return on assets, and interest income diversification have positive impacts. In a similar vein, Batir et al. (2017) found that expenses negatively impact technical and cost efficiency in Turkish banks, while loans positively influence efficiency for both conventional and participation banks. Liquidity has also been identified as an important factor, with its effect on scale efficiency being particularly significant. Alrafadi (2020) similarly observed that return on assets positively impacts cost efficiency, while capital adequacy has a positive influence on all three efficiency measures: Cost, allocative and technical efficiencies.

External factors, including market competition and macroeconomic variables, have also been shown to play a significant role in determining banking efficiency. Competition is often associated with higher levels of technical efficiency, as it incentivizes banks to optimize their operations. Tossa (2016) found that competition positively impacted all efficiency measures in Ghana, with the Herfindahl-Hirschman Index showing a positive effect on efficiency scores. Macroeconomic factors like GDP and inflation can negatively affect bank efficiency, as observed by Batir et al. (2017) and Tossa (2016). Dinberu and Wang (2018) also noted that factors such as profitability and management quality positively influenced efficiency, while capital adequacy showed a negative relationship.

The role of bank characteristics, such as capital adequacy, non-performing loans (NPL), and bank size, has been explored in numerous studies. Alipour et al. (2018) found that capital adequacy had a significant and positive relationship with technical efficiency (TE), while non-performing loans negatively affected the performance of conventional banks. Bank size showed mixed results, with some studies, such as Alrafadi (2020) and Tossa (2016), reporting a negative relationship with certain efficiency measures, while others, such as Singh and Fida (2015), observed a positive impact on efficiency, especially in relation to scale efficiency.

Despite the wealth of studies on banking efficiency, inconsistencies in findings regarding the impact of various determinants are evident, likely due to differences in regulatory environments and economic contexts.

In line with previous research, the purpose of this study is to assess banking efficiency in the MENA region by analyzing different efficiency scores and identifying key determinants.

2. DATA AND METHODOLOGY

The input and output variables used to measure efficiency scores are presented here. Also, the internal and external factors that influence banking efficiency are specified.

Concerning the input and output variables, the intermediation approach is adopted. According to this approach, the outputs measure the desired outcome or revenue of banks (measured in dollars), while the inputs represent resources (measured in dollars) used to operate the banks.

The suitable number of input-output variables is determined by meeting the recommended assumption prior to performing DEA (Cooper et al., 2002):

$$N \geq Max\left(I \cdot J, 3\left(I + I\right)\right), \qquad (1)$$

where N = number of $DMUs$; I = number of inputs; and J = number of outputs.

This study specified three inputs (Total liabilities, Operating expenses including employees' expenses, Depreciation, and amortization of tangible fixed assets) and two outputs (Operating income, Total assets except tangible fixed assets), which are depicted in Table 1.

The data were extracted from the banks' balance sheets and income statements. The study focuses on 59 conventional banks in the MENA region from 2019 to 2023 based on data availability, consistency, and operational stability between 2019 and 2023. Certain banks were excluded from conflict-affected countries like Iraq, Syria, Libya, and Yemen due to data unavailability and operational challenges, as well as banks from Saudi Arabia, which predominantly follow Islamic finance principles, to maintain a focus on conventional banking.

Table 1. Input and output variables used in the DEA model

Input 1	Input 2	Input 3	Output 1	Output 2
Total liabilities	Operating expenses	Depreciation and amortization	Total assets except tangible fixed assets	Operating income

Table 2. 59 conventional banks of 11 MENA region countries

Country	N	Bank	Country	N	Bank
Bahrein	1	Ahli United Bank	Lebanon	30	Bank Audi
	2	Alubaf Arab International Bank		31	Bank of Beirout
	3	Arab Banking Corporation		32	Crédit Libanais
Algeria	4	BNP Paribas Al-djazair		33	Saradar Bank
	5	Fransabank El Djazaïr SPA	Morocco	34	Al Barid Bank
	6	Société générale Algérie		35	Attijariwafa Bank
United Arab Emirates	7	Abu Dhabi Commercial Bank		36	Bank of Africa
	8	Bank of Sharjah		37	Banque Centrale Populaire
	9	Commercial Bank of Dubai		38	Banque marocaine pour le commerce et l'industrie
	10	Emirates NBD		39	Crédit Agricole du Maroc
	11	First Abu Dhabi Bank		40	Crédit Immobilier et Hôtelier
	12	National Bank of Fujairah		41	Crédit du Maroc
	13	National Bank of Ras Al Khaimah		42	Société générale Maroc
	14	National Bank of Umm Al Qaiwain		43	CaixaBank Casablanca
	15	United Arab Bank		44	CDG Capital
Egypt	16	Bank of Alexandria		45	CFG Bank
	17	Banque du Caire		46	CITIBANK Maghreb
	18	Commercial International Bank	Oman	47	Bank Dhofar
	19	HSBC Bank Egypt S.A.E.		48	Bank Muscat
Jordan	20	Arab Jordan Investment Bank		49	Oman Arab Bank
	21	Bank of Jordan	Qatar	50	Ahli Bank
	22	Capital Bank of Jordan		51	Commercial Bank of Qatar
	23	Jordan Ahli Bank		52	Doha bank
	24	Jordan Commercial Bank	Tunisia	53	Bank ABC tunisia
Kuwait	25	Al Ahli Bank of Kuwait		54	Amen Bank
	26	Burgan Bank		55	Banque de Tunisie
	27	Commercial Bank of Kuwait		56	Banque internationale arabe de Tunisie
	28	Gulf Bank		57	Banque Tunisie arabe
	29	National Bank of Kuwait		58	Société Tunisienne de Banque
–				59	Tunisian Saudi Bank

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This sample provides a comprehensive representation of the conventional banking landscape in the MENA region, offering insights into efficiency dynamics in a diverse range of economies.

In terms of specifying the internal and external factors, 12 independent variables were selected, consisting of 8 internal factors and 4 external factors, which are anticipated to significantly influence banking efficiency in the MENA region. This selection is grounded in economic theory and supported by empirical studies. The internal factors were drawn from the banks' balance sheets and income statements used in the study. The internal factors are the Return on Assets (ROA), the Bank Size (LnSize), the Capital Adequacy (CA), the Liquidity Ratio (LR), the Loan-to-Deposit Ratio (LDR), the Non-Performing Loans Ratio (NPLR), the Deposits Ratio (DR), and the Operation Cost (OC). The external factors are the Market Concentration Index measured by the Herfindahl-Hirschman Index (HHI), the GDP per Capital (GDPC), the Inflation Rate (IR), and the Unemployment Rate (UR). These factors are defined in Table 3.

2.1. Methodology

This section describes the DEA method used to evaluate the technical efficiency of banks. It also

Table 3. Internal and external factors

Name	Equation
Internal factors	
Return On Asset (ROA)	$ROA = 100 \cdot \frac{Net\ income}{Total\ assets}$
Bank Size (LnSize)	$LnSize = Ln\left(Total\ assets\right)$
Capital Adequacy (CA)	$CA = 100 \cdot \frac{Equity}{Total\ assets}$
Liquidity Ratio (LR)	$LR = 100 \cdot \frac{Total\ loans}{Total\ assets}$
Loan-to-Deposit Ratio (LDR)	$LDR = 100 \cdot \frac{Total\ loans}{Total\ deposits}$
Non-Performing Loans Ratio (NPLR)	$NPLR = 100 \cdot \frac{Non\ performing\ loans}{Total\ loans}$
Deposits Ratio (DR)	$DR = 100 \cdot \frac{Total\ deposits}{Total\ assets}$
Operation Cost (OC)	$OC = 100 \cdot \frac{Operating\ expenses}{Operating\ income}$
External factors	
Market Concentration Index (HHI)	$HHI = \sum_{j=1}^{n} MS_i^2$, where $MS_i = Market\ share\ of\ bank\ i = \frac{Total\ asset\ of\ bank\ i}{\sum_{j=1}^{n} Total\ asset\ of\ bank\ j\ of\ a\ country}$ *n*: number of banks of the given country
Gross Domestic Product per Capital (GDPC)	$GDPC = \frac{GDP}{Population}$
Inflation Rate (IR)	$IR = 100 \cdot \frac{CPT_t - CPT_{t-1}}{CPT_{t-1}}$ *CPI* is a consumer price index of the year
Unemployment Rate (UR)	$UR = 100 \cdot \frac{Unemployed\ individuals}{Working-age\ population}$

explains the Panel Tobit regression model employed to analyze the impact of internal and external factors on banking efficiency.

The DEA model is a deterministic nonparametric method for estimating the technical efficiency of decision-making units. The measurement of efficiency by the DEA model can be done according to two orientations: output orientation, oriented towards the maximization of outputs; and input orientation, oriented towards the minimization of inputs. The DEA method is based on linear programming techniques.

Suppose we have N decision-making units DMU_n for $1 \le n \le N$. Each DMU_n consumes the I inputs $X_n = \{x_{in}/1 \le i \le I\}$ and produces J outputs $Y_n = \{y_{in}/1 \le j \le J\}$.

Consider a DMU_m (for $1 \le m \le N$). The efficiency indicator of the DMU_m is defined by:

$$E_m = \frac{Weighted\ sum\ of\ the\ outputs\ of\ DMU_m}{Weighted\ sum\ of\ the\ inputs\ of\ DMU_m} \Leftrightarrow \quad (2)$$

$$E_m = \frac{\sum_{j=1}^{J} v_{jm} \cdot y_{jm}}{\sum_{i=1}^{I} u_{im} \cdot x_{im}}, \quad (3)$$

where y_{jm}: j^{th} output; x_{im}: i^{th} input; u_{im}: weighting coefficient of the i^{th} input; v_{jm}: weighting coefficient of the j^{th} output.

The efficiency frontier is made up of DMU displaying scores equal to 1. Thus, the relative technical inefficiency of any DMU corresponds to the distance that separates it from the envelope. For each inefficient DMU, the DEA identifies the sources and the level of inefficiency for each of the inputs and outputs. The level of inefficiency is determined by comparison to a single reference DMU or a convex combination of other reference DMUs, located on the efficiency frontier, which use the same level of inputs and produce the same or a higher-level output.

Obviously, the most important problem at this stage is the evaluation of the weights u_{im} and v_{jm}. This is a tricky problem because there is no single set of weights.

The weights for the DMU_m are determined, using mathematical programming, as the weights that maximize the efficiency of the DMU_m provided that the efficiencies of the other DMUs are limited to values between 0 and 1. This is formulated in the fractional program:

$$\max_{u_{im}, v_{jm}} z_m = \frac{\sum_{j=1}^{J} v_{jm} \cdot y_{jm}}{\sum_{i=1}^{I} u_{im} \cdot x_{im}}$$

$$\begin{cases} 0 \le \dfrac{\sum_{j=1}^{J} v_{jm} \cdot y_{jn}}{\sum_{i=1}^{I} u_{im} \cdot x_{in}} \le 1, \ \ 1 \le n \le N \\ u_{im} \ge 0, v_{jm} \ge 0, \ \ 1 \le i \le I, 1 \le j \le J \end{cases} . \quad (4)$$

The objective is to find the weights u_{im} and v_{jm} which maximize the ratio z_m of the DMU_m. Under the constraints, the optimal value z_m^* is in the range from 0 to 1.

This rational formulation poses the problem of the existence of an infinity of solutions $u_m = (u_{1m}, u_{2m}, \ldots, u_{Im})$ and $v_m = (v_{1m}, v_{2m}, \ldots, v_{Jm})$. This problem is overcome by reducing the rational problem to a linear program.

Two models exist in the DEA family: the CCR model, initiated by Charnes et al. (1978), and the BCC model proposed by Banker et al. (1984). The CCR model is used to measure the technical efficiency (TE) of each DMU assuming that the returns to scale are constant, while the BCC model, an extension of the CCR model, decomposes the technical efficiency into two components, the pure technical efficiency (PTE) and the scale efficiency (SE) by considering the variable returns to scale:

$$CCR - Efficiency(TE) = BCC \\ - Efficiency(PTE) \cdot Scale\ Efficiency(SE). \quad (5)$$

To measure TE and its components, PTE and SE, two models are applied, the DEA-CCR program with Envelopment and Orientation-Output and the DEA-BCC program with Envelopment and Orientation-Output, which are presented below.

$$\max_{\eta_m, \Gamma} \eta_m$$

$$s.t \begin{cases} X_m^t \ge X^t \cdot \Gamma \\ \eta_m \cdot Y_m^t \le Y^t \cdot \Gamma \\ \Gamma \ge 0, \ \ \eta_m \in R \end{cases}, \quad (6)$$

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where

$$\Gamma = \begin{pmatrix} \gamma_1 \\ \gamma_2 \\ \vdots \\ \gamma_n \\ \vdots \\ \gamma_N \end{pmatrix}, \quad X_m = \begin{pmatrix} x_{1m} \\ x_{2m} \\ \vdots \\ x_{Im} \end{pmatrix}, \quad Y_m = \begin{pmatrix} y_{1m} \\ y_{2m} \\ \vdots \\ y_{Jm} \end{pmatrix}, \tag{7}$$

$$X = \left(X_1 \ X_2 \ \cdots \ X_N\right) = \left(x_{in}\right)_{\substack{1 \le i \le I \\ 1 \le n \le N}},$$

$$Y = \left(Y_1 \ Y_2 \ \cdots \ Y_N\right) = \left(y_{jn}\right)_{\substack{1 \le j \le J \\ 1 \le n \le N}},$$

$$\max_{\eta_m, \Gamma} \eta_m, \quad \begin{cases} X_m^t \ge X^t \cdot \Gamma \\ \eta_m \cdot Y_m^t \le Y^t \cdot \Gamma \\ E \cdot \Gamma = 1 \\ \Gamma \ge 0, \quad \eta_m \in R \end{cases}, \tag{8}$$

$$\text{where} \quad E = \left(\underbrace{1 \ 1 \cdots 1 \cdots 1}_{N-times} \right)$$

Since the efficiency scores obtained by applying the DEA model belong to the interval [0, 1], it is appropriate to use the panel Tobit model initially proposed by Tobin (1958), which takes into consideration limited and censored dependent variables.

Let y_{it} be the dependent variable representing TE or PTE of a bank i at time t, and X_{it} be the vector of the corresponding independent variables defined by:

$$X_{it} = \begin{pmatrix} x_{it}^1 \\ \vdots \\ x_{it}^K \end{pmatrix}, \tag{9}$$

where x_{it}^1 are the K explanatory variables with $1 \le k \le K$.

As y_{it} is both left and right censored, the appropriate regression model used is the panel Tobit regression model. Two forms of this model can be applied to a latent variable y_{it}^*: the fixed-effects model and the random-effects model.

i) Fixed-effects model (FE): It allows the individual-specific effects a_i to be correlated with the regressors X_{it}, and a_i are included as intercepts; each individual has a different intercept term (a_i term) and the same slopes parameters (β parameters):

$$y_{it}^* = \alpha_i + \beta' \cdot X_{it} + \mu_{it},$$
$$\text{where} \quad \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_K \end{pmatrix}, \quad \mu_{it} \sim\triangleright \mathcal{N}\left(0, \sigma_\mu^2\right), \tag{10}$$

where a_i are individual-specific coefficients; β is a vector of K coefficients;

ii) Random-effects model (RE): It assumes that individual-specific effects a_i are random variables and distributed independently of the regressors X_{it}, a_i are included in the error term, and each individual has the same slopes parameters β and a composite error term $\varepsilon_{it} = a_i + \mu_{it}$:

$$y_{it}^* = \gamma + \beta' \cdot X_{it} + \alpha_i + \mu_{it},$$
$$\text{where} \quad \beta = \begin{pmatrix} \beta_1 \\ \vdots \\ \beta_K \end{pmatrix}, \tag{11}$$
$$\mu_{it} \sim\triangleright \mathcal{N}\left(0, \sigma_\mu^2\right), \quad a_i \sim\triangleright \mathcal{N}\left(0, \sigma_\mu^2\right),$$

where γ – a constant; a_i: random individual-specific coefficients; $\varepsilon_{it} = a_i + \mu_{it}$: composite error; and β – vector of K coefficients.

The variance and correlation coefficient of the composite error are given by:

$$Var\left(\varepsilon_{it}\right) = \sigma_\alpha^2 + \sigma_\mu^2,$$
$$cov\left(\varepsilon_{it}, \varepsilon_{is}\right) = \sigma_\alpha^2, \tag{12}$$
$$\rho_\varepsilon = cor\left(\varepsilon_{it}, \varepsilon_{is}\right) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_\mu^2}.$$

As y_{it} is left censored by 0 and right censored by 1, it is linked to y_{it}^* by:

$$y_{it} = \begin{cases} 0 & if \quad y_{it}^* \le 0 \\ y_{it}^* & if \quad 0 < y_{it}^* \le 1. \\ 1 & if \quad 1 < y_{it}^* \end{cases} \tag{13}$$

In this analysis, the Hausman Test is used to verify whether there is a significant difference between the fixed and random effects estimators.

3. RESULTS

This section presents the results derived from the application of the DEA model. The findings from the Panel Tobit regression model are then reported. Finally, a comprehensive discussion of these results is provided, comparing them with existing literature.

Table 4 shows the CCR technical efficiency (TE) scores and the BCC pure technical efficiency (PTE) scores of the 59 banks over the period 2019–2023, obtained by applying DEA.

Figure 1 shows the evolution of the average TE, PTE, and SE scores of the 59 banks from 11 countries during 2019–2023.

Table 4. TE and PTE scores of the 59 banks over 2019–2023

Bank	2019		2020		2021		2022		2023	
	TE	PTE	TE	PTE	TE	PTE	TE	PTE	TE	PTE
1	0.975	1.000	0.943	1.000	0.908	0.994	0.934	0.981	0.935	1.000
2	1.000	1.000	0.949	0.972	0.931	1.000	0.942	0.988	1.000	1.000
3	0.830	0.973	0.814	0.982	0.782	0.973	0.756	0.946	0.751	0.925
4	0.807	0.830	0.920	0.923	0.858	0.883	0.899	0.906	0.922	0.922
5	0.967	0.969	0.944	0.948	1.000	1.000	0.940	1.000	0.973	0.981
6	0.886	0.895	0.895	0.896	0.923	0.938	0.898	0.902	0.939	0.940
7	0.914	1.000	0.879	1.000	0.768	0.996	0.880	0.990	0.831	0.987
8	0.939	0.950	0.854	0.897	0.851	0.877	0.830	0.873	0.862	0.864
9	0.892	0.968	0.842	0.973	0.860	0.978	1.000	1.000	1.000	1.000
10	0.936	1.000	0.844	1.000	0.846	1.000	0.861	1.000	0.848	0.999
11	0.969	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
12	0.904	0.946	0.827	0.940	0.780	0.955	0.840	0.933	0.891	0.924
13	1.000	1.000	1.000	1.000	0.973	1.000	1.000	1.000	1.000	1.000
14	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
15	0.767	0.829	0.775	0.845	0.738	0.810	0.713	0.763	0.707	0.756
16	0.900	0.910	0.888	0.908	0.839	0.895	0.952	0.952	1.000	1.000
17	0.785	0.863	0.771	0.891	0.775	0.899	0.877	0.905	0.860	0.903
18	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
19	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
20	0.773	0.773	0.753	0.753	0.717	0.723	0.732	0.734	0.700	0.719
21	0.934	0.938	0.898	0.904	0.850	0.864	0.949	0.952	0.963	0.965
22	0.857	0.878	0.828	0.828	0.782	0.782	0.797	0.799	0.710	0.797
23	0.772	0.816	0.761	0.794	0.732	0.769	0.762	0.776	0.772	0.774
24	0.767	0.776	0.758	0.759	0.728	0.731	0.718	0.722	0.709	0.709
25	0.856	0.940	0.808	0.960	0.766	0.938	0.763	0.911	0.781	0.911
26	0.963	1.000	0.955	0.997	0.948	0.981	0.927	0.958	0.912	0.978
27	1.000	1.000	1.000	1.000	0.870	0.985	0.955	0.987	0.989	1.000
28	0.940	0.958	0.880	0.952	0.796	0.939	0.864	0.938	0.814	0.927
29	0.929	0.988	0.877	0.993	0.845	0.995	0.851	0.977	0.820	0.976
30	0.770	1.000	0.751	1.000	0.710	1.000	0.760	1.000	0.690	1.000
31	0.895	1.000	0.809	1.000	0.808	1.000	0.829	1.000	0.815	1.000
32	0.858	1.000	0.828	1.000	0.769	1.000	0.883	1.000	1.000	1.000
33	0.799	0.991	0.741	0.977	0.710	0.973	0.672	0.923	0.786	1.000
34	0.737	0.785	0.713	0.791	0.683	0.771	0.667	0.757	0.657	0.771
35	0.799	0.948	0.777	1.000	0.740	0.918	0.780	0.895	0.797	0.915
36	0.743	0.878	0.758	0.916	0.721	0.885	0.765	0.863	0.792	0.870
37	0.770	0.905	0.757	0.936	0.716	0.890	0.787	0.886	0.816	0.897
38	0.802	0.880	0.775	0.866	0.733	0.837	0.827	0.866	0.843	0.858
39	0.729	0.824	0.705	0.826	0.675	0.801	0.679	0.805	0.694	0.820
40	0.750	0.826	0.735	0.823	0.700	0.799	0.680	0.804	0.691	0.814

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Table 4 (cont.). TE and PTE scores of the 59 banks over 2019–2023

Bank	2019		2020		2021		2022		2023	
	TE	PTE	TE	PTE	TE	PTE	TE	PTE	TE	PTE
41	0.758	0.825	0.755	0.833	0.719	0.809	0.771	0.816	0.801	0.820
42	0.809	0.897	0.805	0.924	0.757	0.893	0.812	0.878	0.858	0.889
43	1.000	1.000	1.000	1.000	0.868	1.000	1.000	1.000	1.000	1.000
44	0.798	0.807	0.796	0.798	0.747	0.756	0.727	0.733	0.692	0.710
45	0.670	0.697	0.679	0.682	0.645	0.657	0.683	0.694	0.696	0.697
46	1.000	1.000	0.924	1.000	1.000	1.000	0.952	1.000	0.930	1.000
47	0.866	0.941	0.835	0.965	0.792	0.937	0.782	0.932	0.759	0.913
48	0.843	0.988	0.824	1.000	0.794	0.987	0.815	0.990	0.824	0.987
49	0.764	0.832	0.779	0.857	0.773	0.861	0.806	0.876	0.862	0.907
50	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
51	0.970	1.000	0.977	1.000	0.961	1.000	1.000	1.000	0.938	1.000
52	0.928	1.000	0.917	0.988	0.931	0.982	0.948	0.988	0.941	0.997
53	0.777	0.778	0.755	0.762	0.705	0.729	0.695	0.741	0.728	0.746
54	0.834	0.834	0.866	0.868	0.758	0.763	0.819	0.821	0.887	0.890
55	0.903	0.908	0.896	0.898	0.913	0.924	0.958	0.965	1.000	1.000
56	0.841	0.870	0.854	0.868	0.901	0.943	0.896	0.896	0.968	0.969
57	0.765	0.771	0.760	0.761	0.721	0.721	0.740	0.740	0.775	0.776
58	0.747	0.768	0.774	0.788	0.812	0.819	0.836	0.836	0.858	0.862
59	0.831	0.858	0.926	0.928	0.837	0.880	0.808	0.856	0.792	0.793
Average	0.814	0.827	0.833	0.839	0.807	0.826	0.822	0.836	0.858	0.862

The average technical efficiency of the 59 banks from 2019 to 2023 is around 90%, indicating that while the banks are generally not operating at optimal efficiency, they still perform at relatively high levels. The low percentage of technically efficient banks (ranging from 12% to 20% over the years) suggests that most banks face inefficiencies in utilizing their resources effectively. Qatari banks, particularly Ahli Bank, show higher TE scores, benefiting from efficient operations and economies of scale, with Ahli Bank operating under constant returns to scale. In contrast, banks in Morocco and Jordan exhibit lower TE scores, primarily due to scale inefficiencies, suggesting they are operating at non-optimal sizes, either too small to leverage economies of scale or too large, resulting in diminishing returns.

In this section, the second stage of the model is performed by taking the TE and PTE scores as dependent variables. Fixed-effects Tobit and random-effects Tobit models on TE and PTE are run. Then the Hausman test is run to choose between the two types of models.

The results of the fixed-effects Tobit model applied to TE are displayed in Table 5.

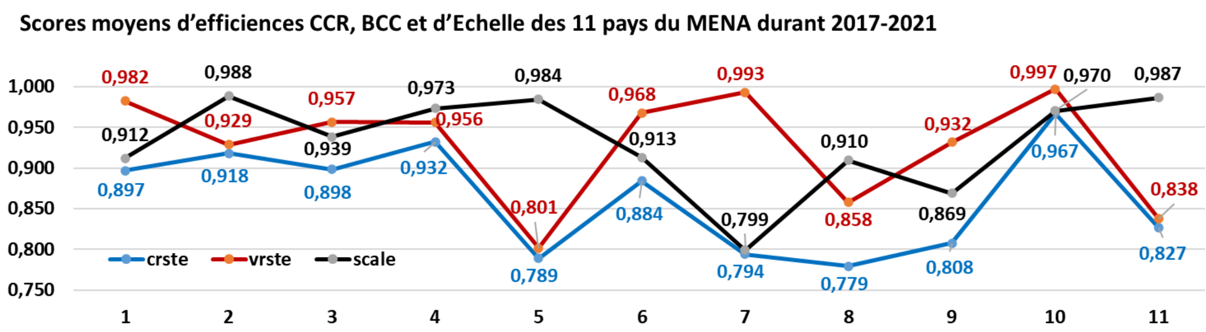

Figure 1. Average TE, PTE, and SE in the 11 countries

Table 5. Results of the fixed-effects Tobit model applied to TE

TE	Coef.	Std. err.	z	P > |z|
ROA	3.956525	.6351973	6.23	0.000
LnSize	–1.213033	.3314899	–3.66	0.000
CA	.7806042	.1080849	7.22	0.000
LR	–.6887565	.1505039	–4.58	0.000
LDR	.4309508	.1030027	4.18	0.000
NPLR	2.431204	.6847686	3.55	0.000
DR	.5935079	.1356431	4.38	0.000
OC	–.1867893	.0355428	–5.26	0.000
HHI	–15.00608	20.38273	–0.74	0.462
GDPC	.0001868	.0000291	6.41	0.000
IR	.0242984	.0233275	1.04	0.298
UR	.1493602	.1603907	0.93	0.352
_cons	56.8817	11.65752	4.88	0.000
var(e.TE)	36.3339	3.34209	–	–

The results of the random-effects Tobit model applied to TE are displayed in Table 6.

Table 6. Results of the random-effects Tobit model applied to TE

TE	Coef.	Std. err.	z	P > |z|
ROA	2.544492	.6976365	3.65	0.000
LnSize	–.2682736	.6031569	–0.44	0.656
CA	.9406658	.1341434	7.01	0.000
LR	–.2248942	.1876687	–1.20	0.231
LDR	.1533095	.1316033	1.16	0.244
NPLR	2.319787	.8080183	2.87	0.004
DR	.3158531	.1727753	1.83	0.068
OC	–.1025105	.0364465	–2.81	0.005
HHI	–14.85234	34.12594	–0.44	0.663
GDPC	.0001347	.0000519	2.60	0.009
IR	.0311311	.0176528	1.76	0.078
UR	.3448789	.1393743	2.47	0.013
_cons	53.39242	16.79555	3.18	0.001
/sigma_u	5.392333	.6903028	7.81	0.000
/sigma_e	4.059998	.2134844	19.02	0.000
rho	.6382072	.067155	–	–

Note: LR test of sigma_u = 0: chibar2(01) = 92.84; Prob. ≥ chibar2 = 0.000.

The Hausman test is applied to determine the appropriate model, with the results presented in Table 7.

Table 7. Hausman test

Factors	Coefficients		(b – B)	sqrt(diag (V_bV_B))
	(b)	(B)		
	RandomTE	FixedTE	Difference	S.E.
ROA	2.544492	3.956525	–1.412033	.2884806
Lnsize	–.2682736	1.213033	.944759	.5038976
CA	.9406658	.7806042	.1600617	.0794489
LR	–.2248942	.6887565	.4638624	.1121075
LDR	.1533095	.4309508	–.2776414	.0819139
NPLR	2.319787	2.431204	–.1114171	.4289353
DR	.3158531	.5935079	–.2776548	.1070152
OC	–.1025105	.1867893	.0842788	.0080661
HHI	–14.85234	15.00608	.1537338	27.37013
GDPC	.0001347	.0001868	–.0000521	.0000429
IR	.0311311	.0242984	.0068326	–
UR	.3448789	.1493602	.1955187	–

Note: Prob. > chi2 = 0.0000.

As the p-value of the Hausman test statistics χ^2 is smaller than 5%, we choose the random-effects Tobit model. The p-value of the statistics χ^2 is equal to 0, indicating that the model is correctly specified.

As shown in Table 6, the ROA, NPLR, DR, GDPC, IR, and UR show a significant positive relationship with TE. The OC exhibits a significant positive relationship with TE. The LnSize, the LR, the LDR, and the HHI exhibit an insignificant effect on TE.

The significant positive relationships between ROA, NPLR, DR, GDPC, IR, and UR with TE suggest that these variables play crucial roles in determining the efficiency of banks. ROA, for instance, reflects the bank's profitability, and its positive relationship with TE implies that more profitable banks tend to be more efficient in utilizing their resources. Similarly, the positive impact of NPLR and DR suggests that banks with higher asset quality and a better deposit base are more efficient.

Economic growth and broader macroeconomic factors such as inflation and unemployment are positively related to TE. This could imply that banks operating in stronger economic environments are better able to optimize their opera-

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tions and manage risks, thus improving their efficiency. For example, higher GDP per capita indicates a wealthier economy with greater demand for banking services, which may allow banks to scale up operations efficiently. On the other hand, inflation and unemployment may push banks to improve operational efficiency as they adjust to economic fluctuations.

The absence of a significant effect from Bank Size, LR, LDR, and HHI suggests that, within the context of this study, these factors do not have a direct impact on technical efficiency. This could reflect the idea that larger banks or those with better liquidity do not always translate into better resource utilization, especially in environments where other factors, like macroeconomic conditions or asset quality, dominate efficiency outcomes. Furthermore, market concentration may not play a significant role if banks in the sample are operating in competitive environments where efficiency is driven more by internal management and operational practices than by market power.

The results of the fixed-effects Tobit model applied to PTE are displayed in Table 8.

Table 8. Results of the fixed-effects Tobit model applied to PTE

PTE	Coef.	Std. Err.	z	P > |z|
ROA	2.671506	.6351278	4.21	0.000
Lnsize	1.886191	.3295951	5.72	0.000
CA	.9125692	.1089797	8.37	0.000
LR	–.7045887	.1476598	–4.77	0.000
LDR	.4690599	.099965	4.69	0.000
NPLR	.9357256	.6718224	1.39	0.164
DR	.584652	.131931	4.43	0.000
OC	–.0786943	.037088	–2.12	0.034
HHI	99.28143	20.11628	4.94	0.000
GDPC	.0001126	.0000302	3.73	0.000
IR	1.02795	.506121	2.03	0.042
UR	.3602111	.1716505	2.10	0.036
_cons	2.609061	11.17989	0.23	0.815
var(e.PTE)	30.67977	3.093076	–	–

Note: Prob. > chi2 = 0.0000.

The results of the random-effects Tobit model applied to PTE are displayed in Table 9.

Table 9. Results of the random-effects Tobit model applied to PTE

PTE	Coef.	Std. Err.	z	P > |z|
ROA	1.80077	.5125784	3.51	0.000
Lnsize	1.893897	.6027094	3.14	0.002
CA	.8326734	.1100339	7.57	0.000
LR	–.2825002	.1495284	–1.89	0.059
LDR	.2021757	.1096238	1.84	0.065
NPLR	1.016058	.6155	1.65	0.099
DR	.3106455	.1437691	2.16	0.031
OC	–.0135521	.0279612	–0.48	0.628
HHI	150.9471	35.81225	4.21	0.000
GDPC	.000068	.0000513	1.33	0.185
IR	.0680406	.1768627	0.38	0.700
UR	.1932502	.1059287	1.82	0.068
_cons	16.38538	15.81562	1.04	0.300
/sigma_u	5.874061	.6917298	8.49	0.000
/sigma_e	2.430599	.1357998	17.90	0.000
rho	.8538119	.032894	–	–

Note: LR test of sigma_u = 0: chibar2(01) = 224.61; Prob. ≥ chibar2 = 0.000.

The Hausman test is applied to determine the appropriate model, with the results presented in Table 10.

Table 10. Hausman test

Factors	Coefficients		(b – B)	sqrt(diag (V_b–V_B))
	(b)	(B)		
	FixedPTE	RandomPTE	Difference	S.E.
ROA	2.671506	1.80077	.8707359	.3750344
LnSize	1.886191	1.893897	–77058	
CA	.9125692	.8326734	798958	
LR	–.7045887	–.2825002	–4220885	
LDR	.4690599	.2021757	2668842	
NPLR	.9357256	1.016058	–803325	.2692676
DR	.584652	.3106455	2740065	
OC	–.0786943	–.0135521	–651421	.0243657
HHI	99.28143	150.9471	–5166569	
GDPC	.0001126	.000068	446	
IR	1.02795	.0680406	.9599093	.4742131
UR	.3602111	.1932502	.1669609	.1350666

Note: Prob. > chi2 = 0.0000.

Since the p-value of the Hausman test statistics χ^2 is smaller than 5%, the fixed-effects Tobit model is chosen. The p-value of the statistics χ^2 is equal to 0, indicating that the model is correctly specified.

As shown in Table 8, all the internal and external factors exhibit significant effects on PTE except the NPLR. The ROA, LnSize, CA, LDR, DR, HHI, GDPC, IR, and UR show significant and positive effects on PTE. The OC and the LR exhibit significant and negative effects on PTE. The NPLR and LR have no significant effect on PTE.

The results of the fixed-effects Tobit model, chosen based on the Hausman test, reveal significant insights into the factors affecting the PTE of banks. The significant positive relationship between ROA, LnSize, CA, LDR, DR, HHI, GDPC, IR, and UR with PTE suggests that these variables play a key role in enhancing a bank's ability to optimize its resources efficiently. For example, higher ROA, which indicates profitability, and greater capital adequacy contribute positively to PTE, reflecting that more profitable and well-capitalized banks can more effectively manage their operations. Larger banks and those with better liquidity management tend to operate more efficiently as well. A stronger economic environment and macroeconomic factors such as inflation and unemployment also have positive effects, indicating that banks in growing economies with stable inflation and low unemployment are more likely to achieve higher PTE.

However, the negative effect of OC and LR on PTE highlights the challenges banks face in managing expenses and maintaining high liquidity while achieving efficiency. High operating costs may detract from efficient resource utilization, while excessive liquidity can tie up resources that could otherwise be used more productively.

Interestingly, the NPLR does not show a significant effect on PTE, which could suggest that asset quality does not necessarily affect a bank's ability to use its resources efficiently, at least not in the context of the current study. This finding could indicate that, for the banks analyzed, managing non-performing loans may not be as critical to achieving pure technical efficiency compared to other factors like profitability and operational costs.

4. DISCUSSION

The findings align with those of several existing studies but also contain contrasts that highlight the unique context of this study.

The results reveal a significant positive relationship between ROA and bank efficiency, confirming that more profitable banks are generally more efficient. This result aligns with studies such as those by Nisar et al. (2018) and Dinberu and Wang (2018), who emphasize the importance of profitability in enhancing efficiency. These studies suggest that profitable banks can better allocate resources and manage their operations, leading to improved efficiency. The results support this idea, demonstrating that banks with higher profitability are better at utilizing their resources efficiently.

The positive effect of DR on efficiency in this study is consistent with the findings of Batir et al. (2017) and Alrafadi (2020). A strong deposit base provides banks with more stable and lower-cost funding, which can lead to improved efficiency in operations. Batir et al. (2017) find that a higher deposit base is associated with better efficiency, a result that is corroborated in this study. This finding underscores the importance of having a solid and diversified funding structure to enhance bank efficiency.

The results show a significant positive effect of CA on efficiency, which supports the findings of Alrafadi (2020) and Alipour et al. (2018). A higher CA ratio allows banks to absorb financial shocks and operate more efficiently by reducing the cost of capital and managing risks better.

The positive impact of LDR on efficiency in this study is in line with the findings of Batir et al. (2017), who suggest that banks with higher LDR ratios tend to be more efficient in utilizing their available resources. LDR indicates how effectively a bank uses its deposits to generate loans, and a higher ratio can suggest better resource utilization, leading to higher efficiency.

It is found that GDPC, IR, and UR have a significant positive effect on PTE, indicating that banks operating in stronger economic environments are more efficient. This is consistent with the findings of Tossa (2016) and Dinberu and Wang (2018), who report that economic factors such as GDP and inflation have a significant influence on bank efficiency. Tossa (2016) emphasizes that macroeconomic factors can push banks to optimize their operations and improve efficiency, especially in times of economic fluctuation, which is reflected in this study.

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The results show that both OC and LR have a significant negative effect on efficiency, which aligns with Batir et al. (2017) and Tossa (2016), who find that high operating costs reduce efficiency. Batir et al. (2017) argue that higher operating costs, such as administrative and operational expenses, reduce banks' ability to utilize their resources efficiently. Similarly, Tossa (2016) identifies the negative impact of operational inefficiencies on banks' technical efficiency, a finding echoed in this study. The negative impact of LR in this study could be explained by the fact that excessive liquidity may indicate inefficiency in resource utilization, as banks may hold more liquid assets than necessary, which could otherwise be used for productive investments.

One notable divergence between the results of this study and previous research is the lack of a significant effect of NPLR on efficiency. Alrafadi (2020) and Alipour et al. (2018) suggest that higher levels of non-performing loans negatively affect efficiency, as they reduce a bank's profitability and increase its risk exposure. However, in this study, NPLR does not show a significant relationship with either TE or PTE. This could be due to the relatively low levels of NPLR in the banks included in the sample or the possibility that banks in the MENA region may have adopted better risk management practices to mitigate the impact of non-performing loans.

This study finds that bank size has no significant effect on efficiency, which aligns with the findings of Singh and Fida (2015), who suggest that larger banks may not necessarily be more efficient. While larger banks might benefit from economies of scale, they may also experience diseconomies of scale, such as management inefficiencies and complexity in operations.

The differences between the findings of this study and those in the literature can be attributed to several factors, including contextual differences such as regulatory, economic, political, and cultural environments, as well as geographical variations. The time period of the studies and the sample composition also play a crucial role in these variations, as the banking environment and the economic conditions might have changed over time, influencing the relationship between the variables and efficiency.

Future studies could investigate the role of digital transformation and technological advancements in enhancing bank efficiency. As banks increasingly adopt digital banking solutions, there could be a shift in the factors that influence efficiency.

CONCLUSION

This study aims to offer a comprehensive analysis of banking efficiency in the MENA region, focusing on 59 conventional banks, from 11 countries namely Bahrein, Algeria, United Arab Emirates, Egypt, Jordan, Kuwait, Lebanon, Morocco, Oman, Qatar, and Tunisia, over the period from 2019 to 2023. The study addresses two main objectives: First, to estimate the technical and pure technical efficiency scores using Data Envelopment Analysis (DEA), and second, to identify the internal and external determinants of banking efficiency through the application of a Tobit regression model.

The DEA model indicates that MENA banks have an average technical efficiency of 90%, with Qatari banks performing the best, while those in Morocco and Jordan experience scale inefficiencies. The Tobit model reveals that ROA positively influences both technical and pure technical efficiency, while capital adequacy has a favorable effect. However, liquidity negatively impacts pure technical efficiency. Operating costs reduce efficiency, and non-performing loans affect technical efficiency but not pure technical efficiency. Macroeconomic factors such as GDP per capita, inflation, and unemployment have a positive impact on both efficiencies.

This study fills a critical gap in banking efficiency research in the MENA region, offering insights for policymakers, regulators, and banks to improve financial system performance. It highlights key efficiency drivers and suggests that policies promoting capital adequacy, risk management, and cost efficiency can strengthen the banking sector. The study also emphasizes the role of macroeconomic stability and proposes avenues for future research, including exploring factors like taxation, regulation, management quality, digital transformation, and exchange rate fluctuations to further understand banking efficiency.

AUTHOR CONTRIBUTIONS

Conceptualization: Soufiane Benbachir.
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Formal analysis: Soufiane Benbachir.
Investigation: Soufiane Benbachir.
Methodology: Soufiane Benbachir.
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Supervision: Soufiane Benbachir.
Validation: Soufiane Benbachir.
Visualization: Soufiane Benbachir.
Writing – original draft: Soufiane Benbachir.
Writing – reviewing & editing: Soufiane Benbachir.

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