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Banking Profitability, Inflation and GDP Relationship: A Monte Carlo Scenario Analysis for Turkey

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ABSTRACT

Economic and political catastrophes have a negative impact on the state budget and the banking industry. The purpose of the study is to assess the impact of macroeconomic factors on the profitability of the Turkish banking sector between 2016 and 2023, using the Monte Carlo method. The study uses the Monte Carlo method with 10, 50 and 100 iterations. The simulation is based on empirical data from the Association of Turkish Banks and the Turkish Statistical Institute, including gross domestic product, inflation, return on equity and return on assets. The results of the study showed that, when using the Monte Carlo model with 100 iterations, the values of ROE and ROA show moderate growth (to an average of 27.68% and 46.94%, respectively) under scenarios of strong economic development, despite the continued instability of inflation, which confirms the presence of stable but sensitive dependencies between variables. According to the findings, there will be no essential changes in the values of the Gross Domestic Product, Inflation values of the state, Return on Equity and Return on Assets values of the banking industry unless correlative relations and volatility (standard deviation) scores can not diminish or balance in 10, 50 and 100 iterations. The importance of macroeconomic variables and globalization is presented as a key factor contributing to this situation. On the other side, the period was very hard for Turkey and the banking industry. In the final section, a brief suggestion will be provided in light of the Monte Carlo Simulation Model algorithms.

KEYWORDS: Bank, Banking Profitability, Business Cycles, Monte Carlo Simulation, Economic Growth, Financial Stability, Turkey

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EJEBS

1. INTRODUCTION

The economic balance of Turkey underwent significant changes between 2016 and 2023, influenced by a military coup attempt, the COVID-19 pandemic, and an earthquake. At the same time, the country experienced conflicts and tensions between various forces, including the government and the central bank. These events are critical for the banking industry, which has been forced to balance the tensions between market forces and the needs and expectations of its stakeholders. As Demirel and Ulusoy (2021) explain, the impacts of the COVID-19 period on banking profitability are clearly evident in terms of the CAR (Capital Adequacy Ratio), ROE (Return on Equity), and ROA (Return on Assets), which are key variables or ratios in determining bank profitability. However, according to them, ROE and ROA have relatively less impact, while CAR maintains its position in the banking industry's profitability in Turkey. It should be noted that Capital adequacy helps the financial system absorb negative shocks by reducing the number of bank failures and losses (Rahman et al., 2020). Uslu (2020) statistically explained the importance of human-resource-depended variables and intellectual capital in the ROE and ROA structures in the Turkish Banking industry. Meanwhile, credit risk, loss of income and liquidity are the most critical factors of the COVID-19 period (Shishavan et al., 2021). According to the analysis by Ova (2020), Derbali (2021), and Raza et al. (2022), ROA and ROE are the most effective profitability ratios in the banking industries of Turkey and Morocco. Moreover, Altay (2021) emphasized the importance of CAMELS components, which include Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity, in the banking industry, as well as the relationships between these components and macroeconomic variables in Turkey's sample. Also, Daver (2020) utilises ROA as a profitability indicator in an analysis. Conversely, GDP (Gross Domestic Product) exhibits a positive and explanatory relationship with banking performance (Sayem et al., 2024; Alshadadi et al., 2024; Ghosh & Mondal, 2024; Rehman et al., 2024). Given the importance of GDP, another key variable is inflation. According to Akoi and Andrea (2020) and Almansour and Almansour (2021), banking performance is influenced by the country's inflation rate. Additionally, Alfadli and Rjoub (2020) found a negative relationship between the inflation rate and banking performance (portfolio confirmation and asset diversification) in Gulf Cooperation Council Countries. According to Calışkan and Lecuna's (2020) analysis, inflation, interest rates, and exchange rates play a significant role in shaping the performance of the banking system, with a positive impact on both return on equity (ROE) and return on assets (ROA). Besides these, İlarslan (2020) confirms the important and negative impacts of terrorist acts on the financial markets. Nonetheless, Wu and Cole (2024) stated that inflation and GDP growth played crucial roles and had detrimental impacts on the US Banking crisis between 1977 and 2019. Moreover, Inflation is so critical that states and governments always aim to suppress it through before-forecasting methods to achieve stability (Posta & Tamborini, 2023). Nonetheless, well-anchored inflation expectations also contribute to general financial markets by boosting economies and investments through which banking industries can create new credit and consumer opportunities (Choi et al., 2021). For this reason, the central bank's positioning in the economies of states should be managed efficiently and effectively, and its policies toward financial markets should be transparent and independent (Fratzcher et al., 2020). In particular, independent central bank policies can be vulnerable during inflationary and stagflationary periods and crises (Gnan et al., 2022). In the works of Gupta and Mahakud (2020) and Korneyev et al. (2022), the inflation rate and GDP Growth, which are determined by the central bank's monetary instruments and arrangements, are important components that shape banking performance under the influence of ROE and ROA. Near the GDP growth and inflation, oil and gas prices (Alyousfi et al.,

2021) and financial inclusion (Shihadeh, 2020) have a decisive impact on banks' performance. For example, not only in the Arabic Peninsula but also in other parts of the world, such as Turkey (Katırcıoğlu et al., 2020), banks' performances move in parallel with oil and gas prices, depending on their oil-related businesses. There is a positive correlation between financial inclusion and banks' performance in the MENAP (Middle Eastern and North African Countries).

In light of these arguments, it can be said that the banking system may suffer from the negative effects of the macroeconomic variables of the states. This research aims to empirically evaluate these negatives in Turkey's sample for 100, 50, and 10 years, as well as 53 banks. It attempts to answer the question of what will happen to the Turkish banking system's profitability over 100, 50, and 10 years, in correlation with GDP Growth and Inflation, if the situation of economic components remains unchanged. To reach this purpose, the research can be examined under three titles. In the first title, a literature review is presented. The methodology and data section will be placed in the second chapter. After the methodology and data section, there will be a discussion, conclusion and suggestion section. At the end of the paper, it can be stated that this research is one of the first examples to utilize the Monte Carlo Method for accurate data in the long term, examining the relationships between leading economic indicators and banking profitability indicators.

2. LITERATURE REVIEW

The Monte Carlo simulation method has also received considerable attention in financial literature, with its extensive utilization in various scientific fields. With the explanative power of Monte Carlo Simulations, this research concentrates on the development of a nexus between macroeconomic indicators and banking indicators.

Sanchez et al. (2016) developed a Bayesian approach for the Monte Carlo Method to evaluate operational risk in commercial banking, focusing on mistakes and errors across different branches between 2007 and 2011. Larcher and Leobacher (2005) argued that there are estimation differences between various applications of Monte Carlo Simulation Models in forecasting risk and asset pricing. According to them, scenario selection and the behaviours of randomness are important variables. One of the primary objectives of homo-economicus is to eliminate stochastic movements (randomness) in financial market behaviours. Monte Carlo applications serve as a suitable tool for this purpose. In the works of Dang et al. (2015) and Liberati and Platen (2004), this intention is observed utilization of complex mathematical calculations and transformations in the pricing of the Options. Platon and Constationescu (2014) emphasized the importance of ensuring randomness in Monte Carlo simulations through the use of random numbers, which provide a quasi-understanding or pseudo-understanding of the Monte Carlo simulation models. The primary measure to address randomness is to benefit from statistical distributions, such as the normal distribution (for relatively large samples, characterized by standard deviations and means), the Poisson distribution (for specific measurement units), etc. The boundaries of randomness, a critical element in the Monte Carlo Simulation, are determined by the power of randomness that develops depending on these statistical distributions. At the same time, the Monte Carlo simulation models can be utilized for future-oriented financial plans and calculations. For example, Arnold and Yıldız (2015), Zaman et al. (2017), Colantoni et al. (2021), Igbal and Purwanto (2022), and Saputra et al. (2023) calculated the future value of a complex financial investment considering different risk scenarios framed with various probability measures (randomness). Morales et al. (2013) utilized a Monte Carlo Simulation Model to determine credit banking risk in home equity loans, considering different scenarios for classifying loans as good or bad. Delis et al. (2020) evaluated one of banking CAMEL performances, management, benefiting from a repeated random sampling (Monte Carlo Simulation Model) with a Bayesian Approach in which there are different output variables such as loan values of banks for different purposes of consumers and input variables such as physical variables, employees, deposits and financial capital under four important managerial scenarios. Barros and Wanke's (2014) cost efficiencies of banks can be proved with a Monte Carlo Simulation Model, which resulted in the statistical insignificance of cost efficiency in public banks and foreign banks. On the other side, the statistical significance of cost efficiency in mergers and acquisitions, big banks, deregulated and stressed banks. In general, the banking industry presents a suitable opportunity for Monte Carlo Simulation Models, particularly given the variety of variables, including macroeconomic and international economic factors.

Monte Carlo Models are one of the most powerful statistical tools in various fields of science. For example, Raeside (1976) argued their utilization in medical science. It should be noted that algorithms based on this method provide statistical estimates for any linear function of the solution by performing random sampling of a specific random variable whose mathematical expectation is the expected function (Atanassov & Dimov, 2008). According to Kroese and Rubinstein (2011), a Monte Carlo Analysis can be utilized for i) to generate random objects and processes to observe their behaviour, ii) to estimate numerical quantities by repeated sampling, and iii) to solve complicated optimization problems through randomized algorithms. In designing a Monte Carlo analysis, the events take their describing forces from a scenario or an event. For example, Glasserman et al. (2001) underlined the importance of case, event and scenario creation in a Monte Carlo VAR analysis. The last design of a Monte Carlo method takes a previous form with different forms, Bonate (2001) stated that the sampling distribution of the model inputs should be defined as an a priori, for example, a normal distribution with mean μ and variance σ^2. Monte Carlo simulations can explain the model repeatedly due to its structure, each time drawing a different random set of inputs from the sampling distribution of the model parameters, resulting in a set of possible outputs and highlighting the critical importance of Random Number generation in computer and mathematical sciences. At the same time, the Random Number Generation Process is also known as pseudo-random number generation, and there are different methodologies for producing numbers, such as Quasi-random number generation. Essentially, the Monte Carlo method is an integration of convergence theory, sampling methods and variance reduction techniques (Caflish, 1998). On the other hand, Ferson (1996) underlined the problems of the Monte Carlo methods, clarifying four important points: i) Like most methods based on probability theory, Monte Carlo methods are very data-intensive. Depending on this feature, they usually cannot reproduce results unless a considerable body of empirical information has been collected or the analyst is willing to make several assumptions in the place of such empirical details. ii). Although suitable for handling variability and stochasticity, Monte Carlo methods cannot be used to propagate partial ignorance under any frequentist interpretation of probability. iii). Monte Carlo methods cannot be used to conclude that exceedance risks are no more significant than a particular level. iv). Finally, Monte Carlo methods cannot be used to effect deconvolutions to solve back calculation problems that often arise in remediation planning. There are various utilisations of Monte Carlo Models, such as the Method of Maximum Likelihood, the Method of Moments and Nonlinear Optimisation (Raychaudhuri, 2008). However, the nature of the science branch and the intensity of risk gain importance in this context. In other words, there can be differences between the social sciences, natural sciences, and engineering sciences regarding iteration numbers and random number generation.

If a square matrix A happens to be symmetric and positive definite, then it has a special, more efficient, triangular decomposition. As it is thought, a matrix has two important dimensions regarding triangularity. In a Cholesky decomposition, the standard matrix structure is divided into subparts using a decomposition process that consists of a lower triangular matrix and its conjugate transpose (A = L, where L is a lower triangular matrix and L* is its conjugate transpose).

3. METHODOLOGY

The methodological framework aims to assess the relationship between macroeconomic indicators and banking profitability in Turkey. A simulation-based approach utilizing the Monte Carlo method is employed to assess various economic development scenarios within controlled stochastic environments. The dataset comprises annual observations from 2016 to 2023, sourced from the Turkish Statistical Institute and The Banks Association of Turkey. Descriptive statistics, correlation analysis, Cholesky decomposition, and simulation models with varying iterations (10, 50, 100) constitute the backbone of the empirical design. The methodology is structured to provide robust insights into the variability and interdependence of GDP growth, inflation, ROE, and ROA.

GDP Growth, Inflation, Average Banking Profitability (ROE), and Average Banking Profitability (ROA) data are provided by the Banks Association of Turkey (ROE and ROA) and the Turkish Statistical Institute for the periods between 2016 and 2023. The variables are listed sequentially in Table 1.

TABLE 1. The variables of the analysis

Year, statıstıcal varıables	GDP growth	Inflation	Banking Profitability (ROE)	Banking Profitability (ROA)
2016	3.318	8.53	8.745	1.729
2017	7.458	11.92	10.258	2.029
2018	3.094	20.3	12.635	2.779
2019	0.862	11.84	8.126	2.829
2020	1.672	14.6	9.355	1.926
2021	11.796	36.08	14.806	3.072
2022	5.308	64.27	32.541	5.109
2023	4.474	64.77	32.926	5.148
AVERAGE	4.748	29.03875	16.174	3.078
STD.DEVIATION	3.520	23.48812188	10.449	1.352
VARIANCE	12.393	551.6918696	109.193	1.830
MIN	0.862	8.53	8.126	1.729
MAX	11.796	64.77	32.926	5.148

Note: compiled by author based on calculations

Using the Excel software package, a Monte Carlo simulation model based on random number generation was implemented. The simulation was carried out for different numbers of observations (iterations-years): 100, 50, and 10. The choice of exactly this number of iterations was made to demonstrate how an increase in sample size affects the stability and visibility of descriptive statistics.

As a result of the simulation, correlation matrices were obtained, reflecting the degree of interrelation among these economic indicators under different sample sizes.

The correlation results presented in Table 2 enable a visual assessment of the strength and direction of the relationships between variables.

TABLE 2. The correlation values of the analysis

Indicator	GDP growth	Inflation	Banking Profitability (ROE)	Banking Profitability (ROA)
GDP growth	1			
Inflation	-0.020457477	1		
Banking Profitability (ROE)	-0.043870175	0.029719616	1	
Banking Profitability (ROA)	0.017011838	-0.028741705	-0.127404127	1

Note: compiled by author based on calculations

The results indicate very weak correlations between macroeconomic variables and banking profitability ratios during the analyzed period (2016-2023), suggesting the absence of strong linear relationships. The strongest — albeit still weak and negative - correlation is observed between Return on Assets (ROA) and Return on Equity (ROE). Notably, inflation and GDP growth exhibit virtually no correlation, further emphasizing the structural independence of these indicators in the current dataset.

Cholesky decomposition is utilised for the correlation matrix, to decompose the correlation matrix (Table 3).

TABLE 3. Cholesky decomposition values of the analysis

Indicator	GDP growth	Inflation	Banking Profitability (ROE)	Banking Profitability (ROA)
GDP growth	1	0	0	0
Inflation	-0.020457477	0.999790724	0	0
Banking Profitability (ROE)	-0.043870175	0.028828176	0.998621221	0
Banking Profitability (ROA)	-0.020457477	-0.029166318	-0.127636771	0.991180948

Note: compiled by author based on calculations

This lower-triangular matrix is used to generate correlated random variables in the Monte Carlo simulations, ensuring consistency with the empirical relationships identified in Table 2. The decomposition reveals that the relationships between macroeconomic indicators and banking profitability metrics remain weak, confirming the results observed in the correlation matrix. While inflation exhibits a minimal negative association with GDP growth, ROE shows slight sensitivity to GDP growth and inflation. ROA demonstrates the most notable – albeit still weak – negative correlation with ROE, as well as minor dependencies on inflation and GDP growth. These patterns justify the use of Cholesky decomposition in the simulation framework, as it preserves the observed structural characteristics while generating correlated random variables.

Thus, based on descriptive statistics, correlation analysis and Cholesky decomposition, the proposed methodology allows the formation of a statistically sound data structure for modelling. Using the Monte Carlo method in various configurations (standard, correlated, and simulated models) provides the ability to assess volatility, stability of relationships, and the behaviour of key macroeconomic and banking indicators, depending on the number of iterations.

4. FINDINGS AND DISCUSSION

The following analysis presents the simulation results obtained using the Monte Carlo methodology. Three models are constructed: the Normal, Correlated (adjusted via Cholesky decomposition), and Simulated (randomly generated values that respect the mean and variance). Each model is executed with 10, 50, and 100 iterations to assess how variability and model stability evolve with increasing sample sizes. The results reflect the behaviour of GDP growth, inflation, and banking profitability metrics (ROE and ROA) across different simulation environments.

In light of the argument above, three statistical models are presented: normal, correlated, and simulated models, along with their averages (arithmetic means), standard deviations (variances), and maximum and minimum values of the simulations for 10, 50, and 100 iterations (years), as shown in Table 4.

TABLE 4. Standard Monte Carlo simulation model

Simulation	Means	Std. Deviations	Maximum	Minimum
GDP growth (%)				
$Normal_{10}$	6.11	4.05	11.86	-0.46
$Normal_{50}$	5.76	3.00	11.86	-0.46
$Normal_{100}$	5.52	3.19	15.91	-0.46
Inflation				
$Normal_{10}$	44.10	28.07	82.58	-20.56
$Normal_{50}$	27.45	27.07	82.58	-53.15
$Normal_{100}$	27.67	25.94	104.15	-53.15
Banking Profitability (ROE)				
$Normal_{10}$	16.22	11.40	35.14	-5.35
$Normal_{50}$	16.11	9.23	35.14	-5.35
$Normal_{100}$	16.31	9.47	42.38	-10.21
Banking Profitability (ROA)				
$Normal_{10}$	2.11	1.83	4.56	-0.59
$Normal_{50}$	2.43	1.42	5.39	-0.59
$Normal_{100}$	2.82	1.31	5.40	-0.59

Note: compiled by author based on calculations

The convergence of the mean values with increasing iterations is revealed through the simulation based on the normal distribution with uncorrelated variables. A moderate reduction in standard deviations is observed, especially for GDP and ROA, indicating an increase in the stability of the distribution. At the same time, negative minimum values of ROE and ROA highlight the presence of hidden volatility in bank profitability indicators even under standard conditions.

To obtain the Correlated Monte Carlo results, Cholesky decomposition values are utilised on the standard model in Table 5.

TABLE 5. Correlated Monte Carlo Simulation Model

Simulation	Mean	Std. Deviations	Maximum	Minimum
GDP growth (%)				
$Normal_{10}$	6.11	4.05	11.86	-0.46
$Normal_{50}$	5.76	3.00	11.86	-0.46
$Normal_{100}$	5.52	3.59	15.92	-0.46
Inflation				
$Normal_{10}$	43.97	28.07	82.39	-20.72

$Normal_{50}$	27.32	27.07	82.39	-53.19
$Normal_{100}$	27.55	25.94	103.96	-53.19
Banking Profitability (ROE)				
$Normal_{10}$	17.20	11.52	35.92	-4.35
$Normal_{50}$	16.62	9.24	35.92	-4.35
$Normal_{100}$	16.84	9.51	43.64	-10.23
Banking Profitability(ROA)				
$Normal_{10}$	-1.38	1.96	4.90	-4.465
$Normal_{50}$	-0.56	1.35	4.90	-4.465
$Normal_{100}$	-0.20	2.05	5.55	-6.00

Note: compiled by author based on calculations

Taking into account the correlation structure through the Cholesky decomposition introduces refinements in the distributions of variables. While maintaining the general dynamics, there is a slight increase in the average ROE values and an increase in the volatility of ROA. In short horizons (10 and 50 iterations), the average ROA value becomes negative, reflecting the vulnerability of bank profitability, even with weak relationships between macroeconomic variables.

Table 6 below presents the results of a simulated Monte Carlo model based on random values, which preserves the empirical means and variances but does not impose a correlation structure between the variables.

TABLE 6. Simulated Monte Carlo Simulation Model

Simulation	Mean	Std. Deviations	Maximum	Minimum
GDP growth (%)				
$Normal_{10}$	25.06	12.96	43.43	4.04
$Normal_{50}$	23.93	9.59	43.43	4.04
$Normal_{100}$	20.72	12.93	56.37	4.04
Inflation				
$Normal_{10}$	1168.71	728.40	2165.68	-510.10
$Normal_{50}$	736.80	702.41	2165.68	-1352.57
$Normal_{100}$	609.75	450.24	2725.21	-1352.57
Banking Profitability (ROE)				
$Normal_{10}$	179.28	109.17	356.57	-24.90
$Normal_{50}$	173.79	87.55	356.57	-27.72
$Normal_{100}$	175.85	90.12	429.64	-80.58
Banking Profitability(ROA)				
$Normal_{10}$	1.00	2.66	6.70	-3.05
$Normal_{50}$	2.08	2.58	9.27	-3.05
$Normal_{100}$	2.56	2.70	10.13	-5.07

Note: compiled by author based on calculations

To obtain the Simulated Monte Carlo model results, the values are arranged to reflect average and variance values, ensuring that the originality of the standard model is not disrupted. The results are derived from the vast numbers of Monte Carlo Simulation models, which sample randomly according to the law of random numbers. The model without equilibrium disturbances has higher volatility than the usual and correlated simulations. Thus, the standard deviation of inflation reaches 728.40 after 10 iterations and remains at 450.24 even after 100 iterations, while the same indicator did not exceed 28.07. For ROE, the standard deviation is 109.17 after 10 iterations, while in regular models it is 11.40. The values of profitability (ROE and ROA) vary widely, with minimum values of -80.58 (ROE) and -5.07 (ROA), indicating the presence of extreme fluctuations. Unlike the models that observe correlation (Table 5), the simulated model of economic theory is poorly interpretable, indicating the need to create an empirical structural dependence when analyzing the probabilistic trajectories of macroeconomic indicators.

Research Scenarios

At this stage, there are three development scenarios: weak, mild, and strong, which are randomly named. In the weak development scenario, there is a 0.1% increase in GDP growth, a 3% decrease in inflation, and a 1% increase in both the ROE and ROA banking profitability ratios, as shown in Table 7.

TABLE 7. Correlation and Cholesky decomposition (in parenthesis) result in weak economic development

Indicator	GDP growth	Inflation	Banking Profitability(ROE)	Banking Profitability(ROA)
GDP growth	1			
Inflation	-0.020(-0.020)	1 (0.999)		
Banking Profitability (ROE)	-0.045(-0.045)	0.029(0.028)	1 (0.998)	
Banking Profitability (ROA)	0.018 (0.018)	-0.029(-0.029)	-0.127 (-0.126)	1(0.991)

Note: compiled by author based on calculations

The correlation matrix, with elements of the Cholesky decomposition under the weak scenario, reflects minor deviations from the basic structure (see Table 3). The most noticeable change concerns the coefficient between ROA and ROE, which remains negative (-0.127) and demonstrates the stability of the relationship between the indicators of bank profitability, even with minimal macroeconomic shifts (0.1% GDP growth and a 3% decrease in inflation). In the mild development scenario, there is a 0.5% increase in GDP growth, a 4% decrease in inflation, and a 2% increase in both ROE and ROA. The overall structure of dependencies retains weak intensity and low correlation connectivity.

The correlation and Cholesky decomposition results are given in Table 8.

TABLE 8. Correlation and Cholesky Decomposition (in parenthesis) result in mild economic development

Indicator	GDP growth	Inflation	Banking Profitability (ROE)	Banking Profitability (ROA)
GDP growth	1			
Inflation	-0.019(-0.019)	1(0.999)		
Banking Profitability (ROE)	-0.045(-0. 045)	0.028(0.028)	1(0.998)	
Banking Profitability (ROA)	0.018(0.018)	-0.0309(-0.0306)	-0.128 (-0.126)	1(0.991)

Note: compiled by author based on calculations

In an intense development scenario, GDP growth increases by 1%, inflation declines by 5%, and the return on equity (ROE) and return on assets (ROA) rise by 3%. The moderate scenario, with a 0.5% increase in GDP, a 4% decrease in inflation, and a 2% increase in bank profitability, results in negligible changes to the correlation structure. The correlation coefficients between the main variables remain close to those observed in the weak scenario: the correlation between ROA and ROE is –0.128, and between inflation and ROA is –0.0309. These values indicate a low sensitivity of correlation relationships to moderate economic shifts and emphasize the structural stability of the system.

The Correlation and Cholesky Decomposition results are given in Table 9.

TABLE 9. Correlation and Cholesky decomposition (in parenthesis) result in strong economic development

Indicator	GDP growth	Inflation	Banking Profitability (ROE)	Banking Profitability (ROA)
GDP growth	1			
Inflation	-0.021 (-0.021)	1(0.999)		
Banking Profitability (ROE)	-0.049 (-0.049)	0.028(0.027)	1(0.998)	
Banking Profitability (ROA)	0.072 (0.072)	-0.019(-0.017)	-0.048(-0.043)	1(0.996)

Note: compiled by author based on calculations

The scenario with 1% GDP growth, 5% inflation reduction and 3% increase in bank profitability leads to an insignificant strengthening of the relationships. The correlation between ROA and ROE decreases in absolute value to -0.048, and the relationship between inflation and ROA weakens to -0.019. At the same time, the positive correlation between GDP and ROA increases to 0.072, indicating the initial manifestation of a more transparent relationship between the real sector and bank profitability under significant economic growth.

Simulated Monte Carlo Simulation model results for 10, 50 and 100 days (iterations) are given in Table 10.

TABLE 10. Simulated Monte Carlo Simulation Model Results

Simulation	Mean	Std. Deviations	Maximum	Minimum
GDP growth (%)				
$\text{Weak}_{10;\,50;\,100}$	24.96; 23.88; 23.14	12.78; 9.53; 10.16	42.22; 42.22; 56.27	4.04; 4.04; 4.04
$\text{Mild}_{10;\,50;\,100}$	24.97; 23.88; 23.14	12.78; 9.53; 10.16	41.84; 42.04; 56.26	4.04; 4.04; 4.04
$\text{Strong}_{10;\,50;\,100}$	145.86; 92.66; 93.35	89.84; 86.38; 82.74	959.373; 959.373; 1157.77	-92.14; -94.72; -238.64
Inflation				
$\text{Weak}_{10;\,50;\,100}$	1169.23; 737.01; 742.77	729.40; 702.76; 673.39	2166.09; 2166.09; 2725.72	-515.50;-1352.80; -1352.80
$\text{Mild}_{10;\,50;\,100}$	1174.56; 738.15; 743.30	723.20; 702.04; 672.90	2165.60; 2165.60; 2725.03	-488.40; -1352.23; -1352.23
$\text{Strong}_{10;\,50;\,100}$	471.28; 457.29; 463.04	301.87; 240.54; 247.25	959.37; 959.37; 1157.77	-92.149; -94.72; -238.64
Banking Profitability (ROE)				
$\text{Weak}_{10;\,50;\,100}$	179.27; 173.73; 175.79	109.14; 87.53; 90.11	356.55; 356.55; 429.55	-26.03; -27.75; -80.61
$\text{Mild}_{10;\,50;\,100}$	*179.11; 173.62; 175.68*	*109.70; 87.71; 90.22*	356.589; 356.589; 429.413	-26.29;-28.04; 80.73
$\text{Strong}_{10;\,50;\,100}$	32.83; 26.70; 27.68	18.80; 18.52; 19.85	61.00; 61.00; 74.27	9.48; -25.56; -25.56
Banking Profitability (ROA)				
$\text{Weak}_{10;\,50;\,100}$	1.35; 2.41; 2.88	2.75; 2.57; 2.70	7.15; 9.49; 10.29	-3.00; -3.00; -4.70
$\text{Mild}_{10;\,50;\,100}$	10.85; 10.40; 10.09	5.27; 3.93; 4.19	17.66; 17.90; 23.77	2.216; 2.216; 2.216
$\text{Strong}_{10;\,50;\,100}$	50.47; 48.37; 46.94	24.85; 18.516; 19.736	83.98; 83.98; 111.25	9.87; 9.87; 9.87

Note: compiled by author based on calculations

In the weak and mild scenarios, the values of the indicators are almost identical, confirming the limited impact of minor macroeconomic adjustments on the simulation results. The average ROE fluctuates in a narrow range - from 173.62 to 179.27, and ROA - from 1.35 to 10.85. In the strong scenario, there is a sharp increase in the average ROA to 50.47 (after 10 iterations) and ROE to 32.83, accompanied by high volatility ($\sigma\_ROE = 18.80$; $\sigma\_ROA = 24.85$). Inflation under strong growth demonstrates a sharp decline: average values fall from 1174.56 (mild10) to 471.28 (strong10), reflecting the targeted reduction in inflationary pressure in the model. Such changes indicate the sensitivity of the results to scenario parameters and confirm the validity of the scenario approach in stress testing of bank profits.

If the same period continues with different economic policies, the following arguments can be concluded by Table 8: Weak, Mild and Strong economic development strategies have negative impacts on GDP Growth. On the other hand, all of the policies have a positive impact on inflation. ROE and ROA values are also positively affected by the randomly generated policies.

The correlative structure and high standard deviations in the research models indicate that volatility structures will exist in the model for the research period, consistent with the findings of Cariolle (2012). Numerous shocks can influence a country's market structure, and according to a substantial body of literature, the volatility-producing financial and economic structures are often a source of ambiguity in microeconomics, macroeconomics, and international economics. Tzeng (2023) uses this inference in its work on the Asian Markets affecting processes by the United States macro variables. On the other hand, Islam (2023) corrects the relationship between banking profitability and the Gross Domestic Product (GDP) relationship. Rakshit (2021) and Shresta (2023) also affirm the relationship between macroeconomic variables and banking industry profitability. The impacts of the countries's globalization are examined by Yakubu and Bunyaminu (2021) found that there is a relationship between the globalization level of countries and banking profitability.

In light of the findings section, it can be concluded that the period between 2016 and 2023 is very hard for Turkey and the Turkish Banking sector. Especially, the magnitude of the various crises will shape the future of the Turkish Financial System. Aksoy et al. (2024) state the destructive impacts of big earthquakes on the fiscal balance of states, and Daniell and Shinozuka et al. (1998) support the idea that earthquakes have re-definitive impacts on the banking and insurance industry. On the other hand, political changes, such as military coups, force states to implement infrastructural measures that are financially and economically feasible due to changing regimes. A military coup can be a cause of the elimination of the trust factor between economic and financial market participants. So, it is a chaotic situation for financial market makers (Lumiajiak et al., 2014; Suwanprasert, 2024). On the other hand, the negatives of COVID-19 are a familiar reality for the finance world.

5. CONCLUSIONS

In light of the above arguments, it can be concluded that policymakers and banking professionals should focus on anticipating and mitigating macroeconomic shocks that contribute to high volatility in key financial indicators. The period from 2016 to 2023 was particularly challenging for Turkey, marked by multiple crises that significantly affected the stability of the banking sector.

The study showed that the profitability of the Turkish banking sector is stable but sensitive to macroeconomic factors, primarily inflation and GDP growth rates. The use of the Monte Carlo method made it possible to identify the impact of different numbers of iterations on the degree of volatility of indicators and scenario changes under weak, moderate, and strong economic development.

The obtained results indicate that if the current economic policy and macroeconomic conditions are maintained, significant improvements in bank profitability indicators are unlikely without reducing volatility and increasing the stability of correlations between variables.

The practical significance of this study lies in the proposed modelling approach, which, based on accurate data, enables consideration of potential risks and instability in strategic planning at the state macroeconomic level and the level of banks' activities. Politicians and financial analysts are advised to pay particular attention to the factors that contribute to macroeconomic shocks, thereby minimizing their impact on the country's banking system.

AUTHOR CONTRIBUTION

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