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RESEARCH ARTICLE

Crisis Monitoring in Financial Sectors Using CAMEL Partial Triadic Analysis Model

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ABSTRACT This study presents the CAMEL Partial Triadic Analysis (CPTA) model, which combines CAMEL methodology with Partial Triadic Analysis (PTA) to evaluate financial indicators on a quarterly basis and delineate risk levels. By analyzing symmetries in data matrices and quantifying vector correlations, the model provides detailed insight into financial trends during recessionary periods, which is useful for financial regulators, public policy makers, and private banking institutions. The CPTA incorporates the commitment matrix, which synthesizes indicator values and provides stability in data matrices in adverse environments. Furthermore, the Fibonacci retracements technique was utilized to categorize variables, identify upward and downward trends, and estimate the solvency of each bank in relation to its respective segment. These results are contrasted using the HJ-Biplot and the dynamic HJ-Biplot, which allow for the evaluation of banking scenarios in the context of financial turbulence. When applied to the Ecuadorian banking sector, the model identified significant fluctuations in three key periods: pre-pandemic, pandemic, and the territorial crisis between Russia and Ukraine. Future research could extend the model by integrating all balance sheet variables against the base CPTA model through the application of Hidden Markov models.

INDEX TERMS CAMEL partial triadic analysis (CPTA), bankruptcy of banks, financial crises, analysis of three-way tables, STATIS.

I. INTRODUCTION

Over the years, the global economic landscape has been marked by several crises. By altering the global economic equilibrium, these disruptions have invariably affected the financial metrics of banking entities, modifying solvency assessments and operational transactions. Among the most significant crises in Latin America and globally were the 1907 crisis, the Great Depression of 1930, the financial meltdown in Asia in 1997, and the collapse of Lehman Brothers in 2008.

The 1907 financial crisis resulted in the failure of approximately 50 banking institutions and 16 trust companies in New York [1]. Research by Tallman and Moen [2], along with that of Nason and Tallman [3], highlights several converging factors that precipitated this crisis, including seasonal fluctuations in liquidity, anomalies in gold flows, a lack of exchange instruments, and a tightening of the credit supply.

Furthermore, Donaldson notes that the crisis was exacerbated by a consolidation of financial power, particularly among dominant banks. This concentration provided defensive benefits to these banks in times of adversity, but also amplified systemic vulnerabilities [4]. The 1907 lessons serve to illustrate the necessity for the implementation of appropriate regulation and the designation of an ultimate lender, in order to guarantee financial stability during periods of uncertainty.

During the Great Depression, the number of banks in the United States dropped from 24,000 in 1929 to 14,000 by 1933. Richardson attributes this decline to the inaction of the Federal Reserve, in conjunction with

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the reciprocal relationship between recession and asset devaluation. [5]. Carlson posits that the banking collapse revealed significant deficiencies in liquidity and solvency, profoundly destabilizing the financial sector and leading to the closure of both insolvent and previously solvent banks [6]. From 1930 to 1933, the U.S. credit system was significantly impaired, characterized by mounting costs and constrained credit accessibility [7].

On a global scale, the Great Depression had a significant impact on trade and investment. In Latin America, Brazil, a major coffee exporter, experienced a precipitous decline in both prices and demand [8]. In addition, throughout the 1930s, domestic credit in the United Kingdom faced restrictions due to adherence to the gold standard pegged to the pound sterling, which limited the country's monetary policy flexibility and exposed the economy to balance of payments volatility.

In July 1997, the Asian financial crisis commenced in Thailand and Malaysia and subsequently spread rapidly throughout the region. Desomansak et al. observed that the effects of the crisis varied considerably from country to country. They emphasized the specific vulnerabilities of Asia's less developed economies and demonstrated the interconnectedness of global markets [9].

In examining the 2008 Lehman Brothers crisis, Fukač observed that the implementation of tighter lending standards between 2006 and 2013 had a significant negative impact on GDP during the recession. Conversely, the subsequent relaxation of these standards facilitated the recovery [10]. Zhariev et al. examine the impact of bank insolvency and the policies implemented in response to the Lehman Brothers failure, extending to the present day, using a bank stress testing model. This model simulates a range of potential stress scenarios, risk management strategies, and measures bank solvency and liquidity. The results indicate the effectiveness of various crisis management measures in maintaining the stability of the banking system and ensuring working capital adequacy under uncertainty [11].

The global economic downturn that emerged in March 2020 as a consequence of the COVID-19 pandemic resulted in a 3.5% decline in global gross domestic product (GDP). This decline was observed in several countries, among them China, the United States, and the Eurozone, as well as Brazil and Ecuador. In these countries, GDP decreased by 2.0%, 3.2%, 3.2%, 3.2%, 7.3%, and 7.2%, respectively, as a consequence of national policies and WTO regulations [12].

In their study, Coibion et al. sought to investigate the relationship between income inequality and household debt over the 2000-2012 (COVID-19). The researchers employed data from the Consumer Credit Panel. The findings indicated that regions with high income inequality exhibited lower levels of household debt accumulation and were more susceptible to higher prices and constrained access to credit. This implies a disproportionate allocation of credit towards high-income households [13].

Meanwhile, in the financial sector, alterations were observed in bank soundness metrics and perceptions. According to Chodnicka, there was a decline in bank soundness, which is likely attributable to changes in financial guidelines. Additionally, there was a shift in the valuation of financial indicators, with diminished emphasis on capital ratios and heightened focus on aspects such as income and liquidity. [14].

Fischer described the observable effects in such crises, including inflation, budget deficits, and unbalanced foreign exchange markets, all of which constrain growth [15] Additionally, the limited fiscal capacity to address the pandemic led to continued foreign borrowing. The elevated interest rates caused by the US Federal Reserve's rate hikes have further exacerbated the external debt of public budgets [16].

In a more focused approach to our research, Ecuador offers a particularly instructive case because it is a South American country that had already experienced a financial crisis between 1998 and 1999. This previous scenario led to the adoption of dollarization in 2000 as an economic policy. The 2020 global pandemic further exacerbated these pre-existing economic vulnerabilities. In this context, Ecuador obtained a €4.2 billion Stand-By Arrangement (SBA) through the International Monetary Fund (IMF).[1] The objective of this agreement was to stimulate economic growth while bolstering the nation's financial resources.

The territorial crisis between Ukraine and Russia has not significantly contributed to global GDP, yet it has a profound impact on global financial markets, particularly in the commodity and energy sectors. Collectively, Russia and Ukraine account for approximately 30% of the global wheat production in 2021, 17% of corn, and 11% of its natural gas and oil production [18]. The conflict resulted in the European Union being unable to access Russian oil and gas, thereby disrupting global supply chains and commodities markets. The inflationary pressures and rising prices had a deleterious effect on macroeconomic stability, global economic expansion, and the political stability of countries that were already contending with the the difficulties posed by the COVID-19 pandemic. In the face of persistent economic instability, banks are exposed to a range of financial disturbances, necessitating continuous monitoring and regulation. [19]. A banking crisis can have a cascading effect, spreading from the banking sector to other levels of the economy, including cities and entire regions or countries. This phenomenon is known as "contagion" [20].

In periods of economic turbulence, the existing regulatory framework for addressing minor banking insolvencies is inadequate for large banks. These institutions' financial health deteriorates, as evidenced by reductions in capital, compromised asset quality, and poor management practices [21].

[1]The SAF is a financing mechanism designed to assist countries facing balance of payments problems due to structural weaknesses or an economy in recession with balance of payments imbalances [17].

In the context of global challenges, such as the ongoing COVID-19 crisis and the heightened tensions between Ukraine and Russia, the financial sector requires an accurate method to evaluate the financial health of banks.

One principal technique CAMELS method, a regulatory assessment framework developed in the United States during the 1970s, is employed to evaluate the financial strength of banking institutions. The CAMELS methodology was developed by the Federal Deposit Insurance Corporation (FDIC), the Federal Reserve, and the Office of the Comptroller of the Currency (OCC) [22].

The system was designed to assess six fundamental elements: capital, asset quality, management, earnings, liquidity, and market sensitivity. It is of paramount importance for the supervision and regulation of banks, ensuring their stability and soundness. Risk-oriented management serves to mitigate and minimize the potential for financial crises to have a detrimental impact on the banking system [23].

A. STATEMENT OF PROBLEM

The identified **research gap** pertains to the limitations of the CAMELS model in accurately comparing the financial indicators, I_k, of J_k banks across different quarters, k, within a given period, T_i. A variety of statistical and mathematical models may be employed, including regression, logistic regression [24], generalized method of moments (GMM) [25], multi-criteria decision-making models (MCDM) [26], and numerous other mathematical and statistical models. Nevertheless, significant challenges remain in developing models that can effectively assess financial health over time in the context of financial uncertainty and crises.

To address the limitations of the CAMEL model, we have integrated the Partial Triadic Analysis (PTA) model into the CAMELS methodology, we have structured a set of $\boldsymbol{X}_k$ matrices, we have constructed a set of $\boldsymbol{X}_k$ matrices, each of which contains I_k rows representing banks and J_k columns representing financial indicators. These matrices are arranged in a way that allows comparisons across different k quarters. The value of T_i determines the agglomeration of the matrices, which is used to assess financial crises. This is a special application of Tucker's Three Mode Factor Analysis.

The application of the CPTA model using the CAMEL or CAMELS methodology is a viable approach, although in this case the S component has been excluded due to the lack of information available in our research.

The financial soundness of banks represents a significant challenge for financial experts, who frequently employ Principal Component Analysis (PCA) to ascertain the relevance of financial indicators and determine the weights (α) assigned to each CAMELS indicator in the period T_i [27]. This approach makes comparison between periods difficult due to divergences between factor axes between quarters. The Partial Triadic Analysis (PTA) generates a factorial axis common to k quarters, thereby facilitating the comparison of the evolution of financial indicators throughout the period T_i.

The research presents a novel approach to examining the crisis of the COVID-19 pandemic and the territorial crisis of the Russian-Ukrainian war on banks' financial indicators. The study examines how banks adjusted their strategies regarding the performance of their financial indicators in response to the crises. The study situates the Ecuadorian banking sector, which operates under a dollarized regime, as a unique setting for examining the financial repercussions in South American emerging markets.

This study **contributes** to the enhancement of the CAMEL methodology. Firstly, the length of the T_i period is statistically validated to ensure its validity. This methodology enables the identification of the effects of the crisis on banks by detecting changes in the financial indicators that exhibited significant alterations in the quarters k that constituted the period of uncertainty, designated as T_2.

Secondly, the relative importance or weight of these financial indicators, as determined by the CAMELS methodology, is assessed in the period under consideration using the Partial Triadic Analysis model. This model assesses the relevance of each indicator based on objective data, rather than relying on subjective criteria, which can be augmented by the input of financial experts.

Third, the determination of the Compromise Matrix, C_{ij}, represents the values of financial indicators I_k of banks J_k over the period T_i, captures the stable structural characteristics of the financial indicators, as well as the level of support and resistance.

Fourthly, we integrate the Biplot representation [28] y HJ-Biplot Galindo of the commitment matrix, which allows the visualization of the relationships between observations (banks) and variables (financial indicators). This provides a common framework of factor axes. This technique enables the interrelationships between banks and indicators to be highlighted on the same dimensional plane, as well as the correlations between variables. This provides a scenario during T_i that reflects fluctuations or crises in the financial sector.

B. OBJECTIVES OF STUDY

The following are the objectives of this study:

- Determine whether the financial indicators that make up the CAMEL Partial Triadic Analysis (CPTA) model have undergone significant changes during the periods T_i: before the pandemic (T_1), during the pandemic (T_2), and during the Russia-Ukraine territorial crisis (T_3).
- The objective is to determine the weights or loadings of the coefficients that make up the ratios of the CAMEL methodology in relation to the impacts of the T_i crisis periods that make up different quarters k. This is to assess the relevance and financial strategies used to deal with these scenarios, with a particular focus on the periods of the (T_2) and the (T_3) crises.
- To establish a graphical representation of the scenarios faced by the banking sector, in collaboration with the

banks and financial indicators, in the context of the impacts of the crises.

- It is necessary to identify both upward and downward trends in the performance levels of the J_k financial indicators that make up the CAMEL methodology.

II. LITERATURE REVIEW

In accordance with the observations presented in the preceding section, it is imperative to implement early warning systems that are designed to assess the conduct of banks within the context of finance and to facilitate the implementation of corrective measures aimed at the identification and mitigation of financial risks.

A. MONITORING FINANCIAL INDICATORS

With regard to this issue, Riasanovsky made a seminal contribution to understanding that in countries exhibiting moderate backwardness, banks serve as substitutes for financial markets with regard to industrialization [29]. Beamer examines financial ratios and assesses the probability of failure and nonfailure [30]. Altman identifies troubled firms using discriminant analysis [31].

The Federal Reserve System (1998) made selections from the financial literature and financial ratios to examine 30 financial structure variables, which proved to be the most useful way of estimating a bank's CAMELS rating and probability of failure. This model was then analyzed using a probit regression model [32].

B. INTEGRATED BANK PERFORMANCE EVALUATION

Cole et al. employed the probit model to forecast the probability of bank failure by analyzing bank indicators. Their findings suggest that the reliability of internal bank ratings diminishes rapidly, necessitating the integration of on-site inspections for more effective supervision [33].

Yuksel et al. conducted a study of Turkish banks between the years 2004 and 2014. The researchers employed multinomial logistic regression to analyze the relationship between the financial indicator ratios of the components of the Camels and the credit ratings granted by Moody's. The findings indicate that an elevated proportion of fixed assets, interest income, and a greater asset market share are correlated with an enhancement in credit ratings. Nevertheless, the analysis revealed the presence of multicollinearity among the variables, which constituted a limitation [34].

C. VARIABLE WEIGHTING IN EVALUATION

In this study, factor analysis was used by Craig to identify the key financial and operational characteristics of banks. These factors were then utilized to develop a logistic regression model, which was used to predict the probability of a bank being put on alert. The results, presented in the form of annually rotated factor matrices, indicated that the factor analysis model, when combined with logit estimation, was effective in identifying troubled banks. Furthermore, the estimated probabilities were found to align closely with the CAMEL ranking [35].

Wanke et al. employed a three-stage design that integrates FAHP, TOPSIS, and neural networks to assess and predict bank performance. FAHP is used to determine the relative importance of criteria based on expert opinion. In turn, TOPSIS evaluates the efficiency of the banks under consideration, employing the aforementioned weights. However, the methodology is not without its limitations. One of these limitations is the complexity of integrating multiple criteria. In addition, the quality of the historical data can affect your analysis [26].

The study conducted by Kočenda et al. employs a meta-analysis approach, synthesizing the findings of 50 previous studies to assess the determinants influencing bank survival or failure. The meta-analysis was performed using the Cox proportional hazards regression model. The results of the study indicate that factors such as asset class and liquidity have a significant effect on the survival of banks. Consequently, the results of this study provide empirical evidence for the relevance of the CAMELS model in providing an empirical basis for bank regulation and management [36].

D. CAMELS INDICATORS IN CRISIS

In their 2002 work, Gasbarro et al. applied the CAMELS methodology to evaluate the Indonesian banking sector over three distinct periods: economic stability, pre-crisis, and crisis. They employed a panel data model to analyze the data. A notable aspect of this study is the use of a continuous measure of bank soundness, rather than the conventional means employed in previous studies. The results demonstrated that during periods of stability, the traditional components of the CAMELS model were able to detect significant changes in the financial indicators of each component. However, during periods of crisis, only the profit component was found to discriminate objectively. Additionally, multicollinearity and heterogeneity issues were identified [21].

E. SOLUTIONS

In order to address the gaps that have been identified, we propose a comprehensive solution that minimises the current limitations. A system of crisis monitoring is proposed for use in the financial sector, utilizing the CAMELS Partial Triadic Analysis Model (CPTA).

The indicator categorization ranges and the weights attributed to these financial indicators are determined by the CPTA model, in contrast to the references [26], [35]. Expert judgment is a valuable tool for corroborating or adjusting these levels.

Furthermore, we address the question raised in the literature [2], [3] regarding the impact of different crises in the banking sector on the financial indicators of the financial sector. To this end, we analyze financial indicators using k quarter integrated T_i time series data. Subsequently, statistical tests are performed to determine whether there are significant changes in certain indicators during the specified periods.

III. MATERIALS AND METHODS

A. CAMEL MODEL AND ITS INTEGRATION WITH PTA

In this study, we utilize the CAMEL framework, as previously introduced, to assess the financial stability of banks. The analysis is centered on five pivotal components: Capital Adequacy, Asset Quality, Management, Earnings, and Liquidity. This is due to the unavailability of data pertaining to Sensitivity to Market Risk.

Although the traditional CAMELS model includes sensitivity to market risk, the methodology remains fully applicable with all five components available, thereby ensuring a comprehensive assessment of the bank's financial health. The flexibility of the CAMEL framework permits the prospective incorporation of the market risk component as data becomes available, thereby ensuring the adaptability of the model to disparate data environments.

From this point onward, we apply the CAMEL framework in our investigation, using the five components to evaluate the financial stability of banks across different quarters k within the periods T_i. The data were organized into matrices corresponding to the pre-pandemic, pandemic, and Russia-Ukraine war periods, and analyzed using the Partial Triadic Analysis (PTA) method. PTA allows for the identification of dynamic trends and common structures across these timeframes, offering a nuanced understanding of financial stability in various contexts within the banking sector.

B. DATABASE

This research utilised data from the Superintendencia de Bancos del Ecuador, which is publicly accessible on the aforementioned institution's website and described in greater detail in reference [37]. The dataset encompasses the period from 2018 to 2023 and encompasses the requisite variables for calculating the financial indicators utilized to validate the analysis of the CAMEL framework. The data offer a comprehensive overview of the financial condition of banks in the BIG segment of the Ecuadorian banking sector.

C. DATA STRUCTURE

As a fundamental component of the analytical process, a data processing step was undertaken to ensure the consistency and comparability of the financial information. The data set was organized into matrices, designated as $\boldsymbol{X}_k$ ($k = 1, \ldots, K$), wherein each matrix represents the financial data for a specific k quarter for the banks in question. Each matrix, designated as $\boldsymbol{X}_k$, comprises $I_k = I(k = 1, \ldots, K)$ rows, representing the banks, and $J_k = J(k = 1, \ldots, K)$ columns, corresponding to the financial indicators subjected to analysis in the study. It was of the utmost importance to guarantee that all matrices retained consistency in their dimensions (I_k, J_k) across all quarters, thus ensuring the comparability of the financial data.

This structure permits a dynamic examination of financial stability across quarters k within time periods T_i, employing a matrix-based approach that monitors the progression of information. The vectorized configuration guarantees dimensional consistency, which is crucial for the implementation of techniques such as partial triadic analysis (PTA). This approach necessitates the uniformity of matrix dimensions for the synthesis and interpretation of data across periods.

PTA employs a comparative and synthetic approach to data, identifying recurrent patterns across multiple data matrices over time. It analyzes the evolution of financial indicators during the pre-pandemic, pandemic, and post-pandemic phases or periods, while capturing the variability and dynamics between them, thereby providing a comprehensive summary of consistent patterns.

D. DEFINITION OF PERIODS

A period T_i, is defined as a grouping of several quarters k in multiple matrices $\boldsymbol{X}_k$, which correspond to phases of crisis or stability in the banking sector. To ensure valid comparisons could be made, both the number of rows (number of banks) and the number of columns (financial indicators) were kept constant across quarters.

The time periods designated as T_i, which correspond to the global health crisis and the Russia-Ukraine conflict, were grouped into k quarters based on their respective durations. The grouping was validated by statistical tests that demonstrated significant fluctuations in financial indicators during the specified periods. In the course of our analysis, the Ti periods were defined as follows:

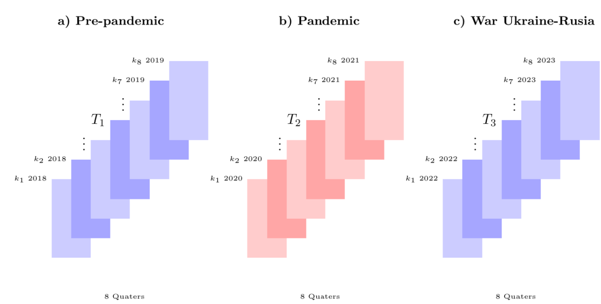


FIGURE 1. Periods: T_i.

- **Pre-pandemic:** T_1: The pre-pandemic period, is defined as the time preceding the outbreak of the pandemic. During this period, economic, social, and political activities were conducted without the disruptions caused by the pandemic. The period of analysis encompasses the interval between the first quarter of 2018 (*March* $_{2018}$) to the fourth quarter of 2019 (*December* $_{2019}$).
- **Pandemic:** T_2: commenced on February 29, 2020, in Ecuador, precipitating substantial disruption to global trade and the international economy, including the banking sector. The period of analysis encompasses the

TABLE 1. Financial indices of the camels model.

Name in short	Measure	Impact
C_1	Solvency	+
C_2	Capital adequacy	+
C_3	Unproductive assets to equity	-
C_4	Net capitalization	+
A_1	Loan delinquecy	-
A_2	Level of absorption	+
A_3	Gross portfolio coverage	-
A_4	Gross loan to assets	-
M_1	Operating efficiency	-
M_2	Personal efficiency	-
E_1	ROA	+
E_2	ROE	+
L_1	Liquidity index	+
L_2	Adjusted liquidity	+

first quarter of 2020 (*March* $_{2020}$) through the fourth quarter of 2021 (*December* $_{2021}$).

- **War Russia-Ucraine:** T_3: The war in Ukraine commenced on February 24, 2022, and has had global ramifications, particularly with regard to inflation and energy prices. This is due to the sanctions imposed by the European Union which limit imports and exports to the Russian market. The analysis period extends from the first quarter of 2022 (*March* $_{2022}$) to the fourth quarter of 2023 (*December* $_{2023}$).

E. DEFINITION OF VARIABLES OF ANALYSIS

Prior to conducting the Partial Triadic Analysis (PTA) and employing the CAMELS methodology on Ecuadorian banks, it is imperative to guarantee the statistical representativeness of the specified period, T_i, as outlined in Section III-D. The table presents an initial set of financial indicators aligned with the CAMELS framework. The analysis is focused on five principal categories: capital, asset quality, management, earnings and liquidity.

Prior to conducting partial triadic analysis (PTA) and applying the CAMELS methodology to Ecuadorian banks, it is of the utmost importance to ascertain the statistical representativeness of the defined period T_i, as discussed in Section III.D. Consequently, Table 1 presents an initial list of financial indicators according to the CAMEL components. The following six categories are to be considered: capital, asset quality, management, results, liquidity.

A comparison of means between periods T_i was conducted to test the null hypothesis, thereby ensuring the validity of the parametric estimation and the grouping of the k quarters. This was accomplished by implementing the normality, homogeneity, ANOVA, and Levene's tests. This approach allowed for the identification of the financial indicators that exhibited significant changes between periods T_i.

F. CAMELS MODEL

The CAMELS model represents a technique that is used to assess the financial performance of banks, serving as an efficient tool for risk assessment, development, and monitoring assets, loans, and equity quality. It aids in identifying and correcting problems. This model employs a quantitative ex-post approach to evaluate bank risk from the perspectives of capital adequacy (C), asset quality (A), management quality (M), earnings (E), liquidity (L), and sensitivity to market (S). It helps identify banks that require special attention from supervisors. In Equation (1), in accordance with the Federal Deposit Insurance Corporation (FDIC) [4], the following weights are applicable:

$$\text{Score} = 0.20\text{C} + 0.20\text{A} + 0.25\text{M} + 0.15\text{E} + 0.10\text{L}L + 0.10\text{S} \tag{1}$$

The application of the CPTA model using the CAMELS methodology is feasible; however, in this instance the S component has been excluded due to a lack of available information. Consequently, the application is limited to the CAMEL methodology.

G. PRINCIPAL COMPONENT ANALYSIS

In this study, principal component analysis (PCA) was employed as a technique to decompose and analyze the structure of the multidimensional financial data derived from the CAMELS methodology. This method, renowned for its ability to linearly reduce data dimensionality [41], emerged as an indispensable tool in our research. It allowed us to project the original dataset, $X = [x_1, x_2, \cdots, x_p]$, into a new subspace with significantly reduced dimensions, $C = (c_1, c_2, \ldots, c_{p<J})$, thereby optimizing the variance of the projected data while maintaining orthogonality constraints [42].

The principal components were identified through linear combinations of the original variables, weighted by coefficients β_{ij}, which represent the contribution of each variable, x_j, to the principal component, C_i, [43]. The relationship was formalized as follows:

$$\begin{aligned} C_1 &= \beta_{11}X_1 + \beta_{12}X_2 + \cdots + \beta_{1J}X_J = Xb_1; \\ C_2 &= \beta_{21}X_1 + \beta_{22}X_2 + \cdots + \beta_{2J}X_J = Xb_2; \\ &\cdots = \cdots + \cdots + \cdots + \cdots C_{i>j} \\ &= \beta_{i1}X_1 + \beta_{i2}X_2 + \cdots + \beta_{iJ}X_J = Xb_i \end{aligned} \tag{2}$$

The first principal component, C_1, is a linear combination of the variables $X_1, X_2, \ldots, X_J$ with the coefficients $B_{11}, B_{12}, \ldots, B_{1J}$. This combination, expressed as $C_1 = b_{1J}$, where b_{1J} is the coefficient vector, maximizes the variance of C_1 under the constraint that the associated normalized eigenvector is of unit length.

Similarly, the second principal component, C_2, is a linear combination of the variables that maximizes the variance under the constraint that C_2 is orthogonal to C_1, expressed as $C_2 = Xb_2$, where b_2 is the corresponding coefficient vector.

This process continues for each principal component, where $C_{p>j}$ is the component that maximizes variance and is orthogonal to all previous components, expressed as $C_{p>j} = Xb_p$, with p less than j and b_p being the coefficient vector. This relationship is succinctly represented in matrix form as the following:

$$C = XB \tag{3}$$

The matrix X represents the original data matrix with dimensions $i \times j$, where i and j are the number of observations and variables, respectively. The matrix of principal components, C, has dimensions $i \times k$, where k is the number of components selected to capture the essence of the information in X. Matrix B contains the factor loadings, which indicate the contribution of each variable to the principal components, with dimensions of j by k.

H. PARTIAL TRIADIC ANALYSIS (PTA) MODEL

In 1978, Jaffrenou first proposed the PTA technique [44]. The technique was employed to measure a time series, organizing the data into tables, with the elements denoted by three indices, $\boldsymbol{X}_{ijk}$, which represent the measurements at station $i(i = 1, \ldots, n)$ for variable $j(j = 1, \ldots, p)$ on date $k(k = 1, \ldots, t)$ [45].

Kroonenberg suggested organizing the data into a series of matrices that reflected the spatio-temporal relationship of each variable, using a distinct matrix for each variable covering months and seasons [46].

Historically, when working with three-dimensional datasets, these were converted into two-dimensional matrices. These matrices were then analyzed using conventional bi-variate analysis methods [47], which is essential for applying PCA.

The fundamental distinction between PTA and the STATIS methods, including X-STATIS, lies in the fact that PTA operates directly on matrices rather than utilizing operators.

I. CAMEL PARTIAL TRIADIC ANALYSIS MODEL (CPTA)

*Definition 1 (**CPTA model**):* The integration of the CAMEL methodology with Partial Triadic Analysis (PTA) allows the derivation of a CAMEL partial triadic analysis model (CPTA) model. This model is based on a set of matrices, denoted by $\boldsymbol{X}_k$, which are composed of I_k rows representing banking entities and J_k columns denoting financial indicators. The aforementioned matrices are employed to analyze data pertaining to a specific time period, designated by T_i, which is divided into k quarters. As long as the number of rows, I_k, and columns, J_k, in all k quarters within T_i are equal, the analysis is valid.

In the CPTA model, the vector correlation matrix Rv was calculated during the infrastructure phase. This matrix reflects the similarities of the k matrices within the period T_i. The differences in the change in amplitude of the coefficients of this matrix reflect the impact on the financial environments. This allows for the evaluation of the stability, perseverance, or crisis of the financial sector. Thus, a dynamic approximation to the relationships within the period ti can be obtained.

In this phase, a Principal Component Analysis (PCA) was conducted on all the vectorized and normalized matrices in a comprehensive and meticulous manner, resulting in the generation of a single reference axis for all the vectors. A Principal Component Analysis (PCA) plot was then constructed, which facilitates the observation of the underlying dynamics and trends in the data over time T_i.

During the infrastructure stage, a commitment matrix, denoted by $\boldsymbol{C}_{ij}$, was calculated, which summarizes the behavior of the banks' financial indicators over the period T_i. This matrix reflects the stability of the k matrices, which allows for the identification of the limits of the financial indicators at the bank level in the face of changes in the financial environment during periods T_i.

The spectral decomposition of the normalized Compromise matrix $\boldsymbol{N}_{ij}$ is performed, which is equivalent to performing a principal component analysis (PCA). To observe the PCA in two dimensions, the HJ-biplot is utilized to facilitate the visualization of both variables and observations in a single graph. Furthermore, the cosine of the angle formed between two vectors represents the correlation between the variables, while the length of the vector represents the magnitude of the variability of the variable. These aforementioned procedures facilitate the identification of patterns of behavior exhibited by the financial indicators in each scenario or period, T_i.

The financial indicators of the normalized commitment matrix, denoted by $\boldsymbol{N}_{ij}$, are categorized by applying the Fibonacci retracement. This allows for the establishment of performance levels for the financial indicators, thereby consolidating a Fibonacci ranking matrix, F. This approach allows for the more effective detection of anomalies in the indicators, since it does not depend on a normal distribution.

Each column of the Fibonacci ranking matrix is influenced by the unified loading vector $\boldsymbol{\rho}$, resulting in the weighted matrix W. The matrix W represents the level of each financial indicator achieved, with the degree of importance of each indicator in the CAMELS component determining the weighting. This matrix serves as the foundation for determining the banking ranking of each bank over the evaluated period T_i.

IV. EXPERIMENTAL SETUP: CPTA MODEL

A. DESCRIPTIVE STATISTICS OF FINANCIAL INDICATORS

A series of statistical analyses were conducted to evaluate the centrality, dispersion, and shape of the distribution of financial indicators. These assessments were applied to the consolidated matrices, $\boldsymbol{X}_k$, of several quarters, k, that constitute each period, T_i. The statistical analyses included the calculation of the mean, median, standard deviation, skewness, and kurtosis. This method enables the detection of significant anomalies in financial data.

Table 15, located in the Appendix, reveals significant trends in the financial indicators, J_k, across various periods, T_i, including pre-pandemic T_1, pandemic T_2, and T_3.

Prior to the onset of the pandemic, indices such as A_1 and A_2 exhibited notable stability, with means of 84.91 and 5.38, respectively, and relatively moderate standard deviations. The stability of the indices was disrupted during the pandemic period. The mean of A_1 decreased to 80.75, and its standard deviation increased to 8.55, indicating heightened volatility.

Moreover, it was observed that the values of the variables in question underwent significant changes. During the pandemic, the maximum value of A_1 exhibited a slight increase to 91.55, indicating the emergence of outliers, potentially due to exceptional conditions during this period. This pattern was observed to be consistent across other indices, indicating a general trend towards increased variability.

The skewness and kurtosis also provided insights that were valuable. The negative skewness of A_1, which intensified during the pandemic (-1.57), suggests a distribution that is skewed leftward. At the same time, an increase in kurtosis, particularly for indices such as A2, during the pandemic (5.66), indicates heavier tails in the distribution.

Finally, during the period of the Russia-Ukraine war, the means of the C_1 and C_2 indices increased to 8.24 and 4.73, respectively. Nevertheless, considerable variability was observed in the central tendency and dispersion metrics, reflecting the uncertainty that pervaded this period.

B. STEP ZERO: MATRIX PREPROCESSING

In this initial phase, a number of preliminary tasks were required before proceeding with experimentation with the CPTA models. These tasks are described in Figure 3.

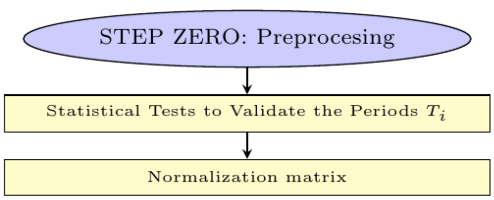


FIGURE 2. Step Zero: Pre-processing.

1) STATISTICAL TESTS TO VALIDATE THE PERIODS T_I

In order to apply the CPTA model and assess significant changes in financial indicators during the periods T_i: The pre-pandemic period ($T1$) is defined as the time preceding the outbreak of the pandemic, during which economic, social, and political activities were conducted without the disruptions caused by the pandemic pandemic (T_1), during the pandemic (T_2) and the Russia-Ukraine war, a structured set of statistical tests was required. These included normality tests, homogeneity of variations tests, and ANOVA means tests, as well as Levence's test.

2) MATRIX DATA

*Definition 2 (**Matriz** $\boldsymbol{X}_{[k]}$):* The array of financial data matrices, designated as $X_{[k]}$, corresponds to quarter k. Each matrix $X_{[k]}$ has I_k rows and J_k columns, where ($k = 1, 2, \ldots, K$). In this context, I_k represents the number of banks and J_k denotes the financial indicators being measured. It is of paramount importance that all matrices designated as $X_{[k]}$ exhibit uniformity with respect to both the number of rows I_k and columns J_k. Each matrix must be organized within the vector space $\mathbb{R}^{I \times J}$.

To elucidate the configuration of the matrix $\boldsymbol{X}_{[k]}$ we will exemplify with the matrix $\boldsymbol{X}_{[1]}$ which represents the financial data relevant to the first quarter of 2018 (specifically March 2018). This particular matrix is situated within the T_1 period of the BIG segment. The matrix has dimensions of 6 x 5, as shown in the equation at the bottom of the next page, where $I_k = 6$ denotes the banks and $J_k = 5$ corresponds to the financial indicators.

3) MATRIX NORMALIZATION

The matrix normalization process for $\boldsymbol{X}_{[k]}$ is conducted in three consecutive phases to standardize the variables and facilitate comparisons between disparate time periods or datasets.

a: CENTERING

This phase entails the calculation of the mean value for each column within the matrix, thereby ensuring that the dataset is centered around the zero. The resulting matrix, designated as $\boldsymbol{X}_{\text{cen}}$, is obtained by subtracting the mean value of each column from the initial matrix, $\boldsymbol{X}_{[k]}$.

b: COLUMN NORMALIZATION

To adjust each variable's standard deviation to 1, each element in $\boldsymbol{X}_{\text{cen}}$ is divided by the standard deviation of its respective column. This step produces the normalized matrix, $\boldsymbol{X}_{\text{norm}}$:

$$\boldsymbol{X}_{\text{norm}} = \frac{\boldsymbol{X}_{\text{cen}}}{\sigma} \tag{4}$$

In this context, the variable σ represents a vector of rows that encompasses the standard deviations corresponding to each column within $\boldsymbol{X}_{\text{cen}}$. This normalization process serves to standardize the variability of each column, thereby addressing any discrepancies in units or scales present between indicators.

c: GLOBAL NORMALIZATION USING FROBENIUS NORM

To ensure uniform matrix magnitude, the Frobenius norm is applied to $\boldsymbol{X}_{\text{norm}}$:

$$\boldsymbol{X}_{\text{Global norm}} = \frac{\boldsymbol{X}_{\text{norm}}}{\|\boldsymbol{X}_{\text{norm}}\|_F} \tag{5}$$

The result of this process is Global Normalization matrix, $\boldsymbol{X}_{\text{Global norm}}$, where the sum of the squares of all elements is equals one:

$$\sum_{i=1}^{m} \sum_{j=1}^{n} X^2_{\text{Global norm},ij} = 1 \tag{6}$$

This exhaustive normalization process facilitates fair comparisons between matrices from different periods or experimental conditions by eliminating differences in scale and ensuring a consistent overall magnitude.

For example, applying this Global Normalization $\boldsymbol{X}$ $_{\text{Global norm}}$ to the matrix from the first quarter of 2018 (March 2018) illustrates the structure and advantages of this method. As shown in the equation at the bottom of the next page.

C. FIRST STEP: INTER-STUCTURE

The interstructure analysis was conducted using the principal component analysis (PCA) technique, which employed the vectorized matrices $\boldsymbol{X}_{[k]}$ as the input. This approach facilitated the identification of structural similarities and differences between multiple sets of vectorized matrices, with the k subindex representing the $k-th$ matrix in each quarter within the period T_i. The application of this methodology ultimately results in the generation of a positive semidefinite matrix, which effectively preserves the intrinsic structure of the data within a lower-dimensional context.

1) VECTORIZED MATRICES

The matrices $\boldsymbol{X}_{[k]}$ were transformed into one-dimensional vectors, represented by $\boldsymbol{S}_{[k]}$, through the subsequent mathematical operation:

$$S_k = Vec(\boldsymbol{X}_{[k]}) = \begin{bmatrix} x_{11}^{(k)} \\ x_{21}^{(k)} \\ \vdots \\ x_{I_k 1}^{(k)} \\ x_{12}^{(k)} \\ \vdots \\ x_{I_k J_k}^{(k)} \end{bmatrix} \tag{7}$$

The initial transformation of each matrix, designated as $\boldsymbol{X}_{[k]}$, with dimensions $I_k \times J_k$, was performed by sequentially aligning all matrix elements in a single vertical sequence. This was achieved by starting with the elements of the first column and proceeding successively up to the last column, designated as J_k. As a result, a column vector was generated, denoted by the symbol $\boldsymbol{S}_k$.

Subsequently, the $\boldsymbol{S}_k$ vectors were integrated to create the $\boldsymbol{Z}$ matrix. This matrix aggregates the vectorized matrices across multiple quarters k within the period T_i analyzed. (8) and (9), as shown at the bottom of page 11.

The D_i matrix has a similar structure to the C_i matrix mentioned above, although it contains non-normalized data.

2) MATRIX STRUCTURE ANALYSIS

The similarity metric, represented as $C_{k,l}$, resemblance a correlation coefficient applicable to square matrices and is commonly identified as the Hilbert-Schmidt inner product. In the framework of Partial Triadic Analysis (PTA), this similarity metric is articulated la vector covariance Covv as:

$$\text{Covv}(X_{[k]}, X_{[l]}) = \text{trace}\ \{X_{[k]}^t \times X_{[l]}\} \tag{10}$$

$$= \text{vec}\ \{S_{[k]}\}^t \times \text{vec}\ \{S_{[l]}\} \tag{11}$$

Similarly, the variance vectorial, Varv of matrix is calculated as:

$$\text{Varv}(X_{[k]}) = \text{trace}\ \{X_{[k]}^t \times X_{[k]}\} \tag{12}$$

*Definition 3 (**Coefficient Similarity Matrix** R_v):* To analyze structural similarities between studies (quaters k), we define the cosine similarity matrix, denoted as R_v. This matrix has dimensions $T_i \times T_i$, where T_i is the number of studies being compared. Each element, $R_v(X_{[k]}, X_{[l]})$, represents the cosine similarity between studies $X_{[k]}$ and $X_{[l]}$. The cosine similarity metric, also referred to as the R_v coefficient, is defined by:

$$R_v\ (X_{[k]}, X_{[l]}) = \frac{\text{Covv}\{X_{[k]}, X_{[l]}\}}{\sqrt{\text{Var}(X_{[k]})\text{Var}(X_{[l]})}} \tag{13}$$

$$R_v = \frac{\text{trace}\ \{X_{[k]}^t \times X_{[l]}\}}{\sqrt{\text{trace}\{X_{[k]}^t X_{[k]}\} \times \text{trace}\{X_{[l]}^t X_{[l]}\}}} \tag{14}$$

$$R_v = \frac{S_{[k]}^t\ S_{[l]}}{\|S_{[k]}\|\ \|S_{[l]}\|} \tag{15}$$

This process entailed a comparison between pairs of matrices, designated as $\boldsymbol{S}_k$, which enabled the simultaneous analysis of all relationships between matrices and facilitated the assessment of their structural similarities and differences. Furthermore, an integrated PCA was performed to examine the evolution of the matrices over time, designated as T_i. [50]

We analyzed the matrix similarities between different units by normalizing the dot product, resulting in a matrix R_v with values from -1 to 1, which facilitates interpretation. We derived a more meaningful measure using the covariance of the centered and scaled vectors [51], which represents their correlation [53].

$$X_{[1]} = \begin{bmatrix} \text{BANCOS} & C_3 & A_4 & & L_2 \\ & & & & \\ \text{Pichincha} & 162.4598 & 50.2934 & \cdots & 23.9103 \\ \text{Pacifico} & 167.2283 & 59.2850 & \cdots & 29.0032 \\ \text{Guayaquil} & 160.8086 & 56.4321 & \cdots & 27.9765 \\ \text{Produbanco} & 184.6454 & 56.3515 & \cdots & 32.8340 \\ \text{Internancional} & 129.5952 & 57.4358 & \cdots & 25.2624 \\ \text{Bolivariano} & 222.7981 & 51.2225 & \cdots & 38.9054 \end{bmatrix}$$

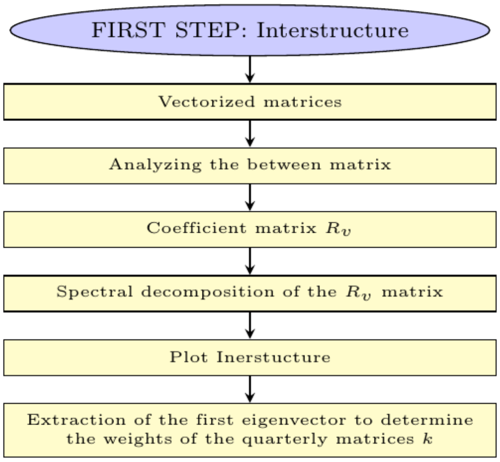


FIGURE 3. **First step: Interstucture.**

The average of the correlation coefficients for the vector k (periods) between $\mathbf{S}_k$ and $\mathbf{S}_{k'}$ is used to determine the vector correlation coefficient $\boldsymbol{R_v}$. The coefficient R_v is defined to range from -1 to $+1$, as it represents the average of a set of correlation coefficients [54].

3) THE CALCULATION OF EIGENVALUES AND EIGENVECTORS FOR PCA

et $X \in \mathbb{R}^{m\times m}$ be a matrix. There exist orthogonal (or unitary) matrices $U, V \in \mathbb{R}^{\nu\times\nu}$ such that $V = range(X)$. Consequently, X can be expressed as follows:

$$\boldsymbol{X} = U\Lambda V^t \tag{16}$$

In this analysis, matrix U was derived from $\boldsymbol{X^t X}$, with its columns representing the eigenvectors. Similarly, matrix V was derived from $\boldsymbol{XX^t}$, also consisting of columns that were eigenvectors. Furthermore,

$$\boldsymbol{\Sigma} = diag(\lambda_1, \lambda_2, \cdots, \lambda_k) = diag\{\lambda_{[k]}\} \tag{17}$$

In the analysis, the diagonal elements were ordered from the largest to the smallest, with the first element being greater than the second, and so on, up to the last element. The singular values of matrix X are designated as positive real numbers, in accordance with the theorem by Eckart and Young [55].

For the symmetric matrix $\boldsymbol{C}$ of dimensions $i \times j$, representing $\boldsymbol{R_v}$ corresponding to period T_i, the singular value decomposition (SVD) simplifies due to the identical vectors of $\boldsymbol{C}$ and $\boldsymbol{C}^t$. Consequently, $U = V$. The spectral decomposition of C was employed to construct a Euclidean representation space for each quarter, k, which was termed "interstructure." This is detailed in:

$$\boldsymbol{C} = U\Lambda U^t \tag{18}$$

4) PCA OF THE INTER-STRUCTURE

A principal component analysis (PCA) was conducted, during which the eigendecomposition of $\boldsymbol{C}$ was employed to analyze the relationships among the quarterly matrices, k, over the period T_i. This process identified key patterns and significantly reduced the dimensionality of the data, thereby preserving essential variations. Principal component analysis (PCA) transformed the quarterly matrices, k, into principal component orthogonal variables, which are crucial for representation in reduced spaces. A PCA map based on the first two columns of F was employed to visualize the matrices' similarities in a two-dimensional space.

$$F = U\lambda^{1/2} \tag{19}$$

5) WEIGHT OF EACH MATRIX DATE FOR A GIVEN PERIOD

Principal Component Analysis (PCA) was employed to examine the underlying structure and relationships between variables over quarters, K, within the period Ti. The initial eigenvector, designated as u_1, was extracted through the process of decomposing the eigenvalues. This vector represents the weights of the quarterly K matrices within the T_i period.

The weights u_1 are of paramount importance, as they provide an optimal representation of the J_k variables within the k quarterly matrices. The first eigenvector, u_1, is then rescaled in such a way that the sum of the elements of alpha equals one [50].

$$\alpha = u_1 \times (u_1^t 1)^{-1} \tag{20}$$

D. SECOND STEP: INTRA-STRUCTURE

*Definition 4 (**Compromise matrix** C_{ij}):* The compromise matrix, $\boldsymbol{C}_{ij}$, having the same dimensions as the individual data matrices with I_k rows and J_k columns, was constructed to synthesize the overall information from various instances, thereby facilitating a comprehensive analysis or comparison across the matrices.

$$X_{[Global\ norm]} = \begin{bmatrix} \text{BANCOS} & C_1 & C_2 & & L_2 \\ & & & & \\ \text{Pichincha} & -0.0569 & -0.2717 & \cdots & -0.2087 \\ \text{Pacifico} & -0.0261 & 0.2293 & \cdots & -0.0235 \\ \text{Guayaquil} & -0.0676 & 0.0703 & \cdots & -0.0608 \\ \text{Produbanco} & 0.0867 & 0.0658 & \cdots & 0.1158 \\ \text{Internancional} & -0.2696 & 0.1262 & \cdots & -0.1595 \\ \text{Bolivariano} & -0.3336 & -0.2200 & \cdots & 1.3366 \end{bmatrix}$$

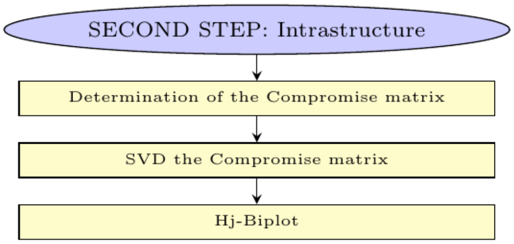


FIGURE 4. Second step: Intrastucture.

In order to obtain the commitment $\boldsymbol{C}_{ij}$ from the original data, the first component of the spectral decomposition U^t is extracted using Equation (18). This captures the largest explained variance and establishes the weights α, which are then assigned to each of the original matrices X_k. Prior to application, these weights are rescaled according to the Equation (20).

With the adjusted weights, the matrix D_i containing the column-vectorized matrices of the different quarters k that compose the non-normalized data period T_i is multiplied by the adjusted vector of weights u_1. This generates the vector Y_i described in equation (21). Finally, the vector Y_i is rearranged into a two-dimensional matrix, called the commitment matrix $\boldsymbol{C}_{ij}$ of order I_k rows (Banks) $\times$ J_k columns (Financial indicators).

$$\boldsymbol{L} = Z \times \alpha \tag{21}$$

$$\boldsymbol{P} = D \times U_1 \tag{22}$$

The sole distinction between the calculation of the normalized commitment matrix, Nij, and that of the original matrix, $\boldsymbol{C}_{ij}$, is the assignment of weights, which is performed using Equation (22). This matrix will later be used as input for the HJ-Biplot.

An alternative approach is the X-STATIS method. The compensation matrix, $\boldsymbol{C}_{ij}$, was obtained by averaging the data matrices, $\boldsymbol{X}_k$, over k periods. This calculation employed scaled weights of the eigenvectors of the underlying matrix structure. Each original data matrix, $\boldsymbol{X}_k$, over k periods, was appropriately scaled in the calculation of $\boldsymbol{C}_{ij}$.

$$\alpha = \sum_{i=1}^{k} \delta X_{[k]} \tag{23}$$

1) SVD OF THE COMPROMISE MATRIX C_{IJ}

To the Normalized Compromise matrix N_{ij} we calculate the spectral decomposition:

$$\boldsymbol{N}_{ij} = U\lambda V^t \tag{24}$$

Factor scores for the observations (banks) were obtained by applying Equation (25), which resulted in:

$$F = U\lambda^{1/2} \tag{25}$$

The consistency of the spectral decomposition was evaluated using the symbol λ, which represents the variance in the components. Furthermore, this method did not provide an adequate approach for structuring a graph to represent the

$$\boldsymbol{Z} = [\boldsymbol{S}_{[1]}, \boldsymbol{S}_{[2]} \ldots, \boldsymbol{S}_{[k]}, \ldots, \boldsymbol{S}_{[k]}] \tag{8}$$

$$\boldsymbol{Z_i} = \left[\begin{array}{ccccc}
k & S_1 & S_2 & \cdots & S_8 \\
 & 1k_{2018} & 2k_{2018} & \cdots & 8k_{2019} \\
 & & & & \\
I_1, J_1 & -0.2847 & -0.2500 & \cdots & -0.6961 \\
I_2, J_1 & -0.1303 & -0.3300 & \cdots & 1.1726 \\
I_3, J_1 & -0.3381 & 1.6800 & \cdots & 1.1288 \\
I_4, J_1 & 0.4333 & 0.1000 & \cdots & -0.3436 \\
I_5, J_1 & -1.3482 & 0.1900 & \cdots & 0.0592 \\
I_6, J_1 & 1.6680 & -1.8700 & \cdots & -1.4222 \\
I_1, J_2 & -1.3586 & 1.0500 & \cdots & 1.2940 \\
I_2, J_2 & 1.1464 & 0.2300 & \cdots & 0.4798 \\
I_3, J_2 & 0.3516 & 0.5500 & \cdots & 0.5260 \\
I_4, J_2 & 0.3291 & 0.1600 & \cdots & 0.0129 \\
I_5, J_2 & 0.6312 & -0.1200 & \cdots & -0.8911 \\
I_6, J_2 & -1.0998 & 1.5600 & \cdots & 1.5957 \\
\vdots & \vdots & \vdots & \cdots & \vdots \\
I_1, J_6 & -1.3546 & -1.3485 & \cdots & -1.2783 \\
I_2, J_6 & 1.4649 & 1.6002 & \cdots & 1.5666 \\
I_3, J_6 & -0.3084 & -0.2306 & \cdots & -0.5675 \\
I_4, J_6 & -0.0727 & -0.3331 & \cdots & -0.0738 \\
I_5, J_6 & 0.7994 & 0.6076 & \cdots & 0.6873 \\
I_6, J_6 & -0.5286 & -0.2957 & \cdots & -0.3343
\end{array}\right] \tag{9}$$

infrastructure of the $\boldsymbol{X}_k$ matrices for the various quarters, k, composing each period, T_i.

2) HJ-BIPLOT

*Definition 5 (**HJ-BIPLOT**):* The goal of BIPLOTS is to provide an approximate graph of data matrices that visually captures the interrelationships between sets of individuals and variables, as well as the relationships between the elements of each set, with a quality of representation that matches their geometric properties [28]. In our study, we applied HJ-BIPLOT (Galindo, 1985), which is a multivariate graphical representation of row and column markers selected so that they can be superimposed in the same reference system with maximum representation quality. This method ensured equal quality of representation for both rows and columns.

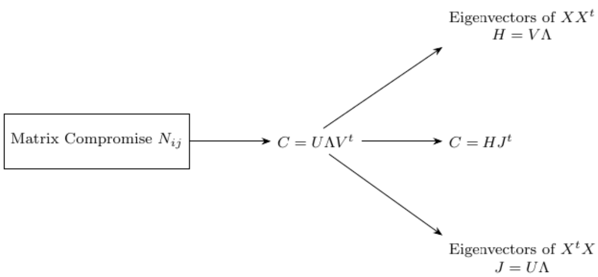


FIGURE 5. HJ Biplot.

The decomposition of the markers in the singular value decomposition was conducted as outlined in:

$$\boldsymbol{C}_{ij} = HJ' = (V\lambda)(U\lambda)' \tag{26}$$

This method was applied to:

$$J = U\lambda \quad H = V\lambda \tag{27}$$

For the study of the HJ-BIPLOT derived from the PCA, it was essential to adopt an interpretation approach that is applicable across all quadrants and encompasses any variable of interest:

- The length of each column vector is indicative of the inherent variability of the financial indicators, which in turn determines their contribution level to the PCA. Longer vectors represent indicators with greater variability or influence.
- The cosines of the angles between the column vectors, representing financial indicators, J_k, indicate the covariation or correlation levels among them. Acute angles suggest positive correlations, obtuse angles indicate negative correlations, and right angles denote no correlation between the variables [57].
- Projecting an individual I_K (bank) onto a specific vector determines its relative position within the original data matrix. Projections on the positive side of the vector suggest performance above the group average, whereas projections on the negative side indicate below-average performance [58].
- The proximity of points in the HJ-Biplot reflects the similarity between entities (banks).

E. THIRD STEP: BANK EVALUATION

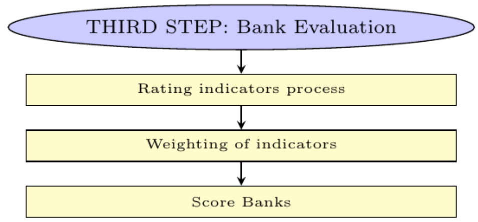


FIGURE 6. Third step: Bank evaluaion.

1) LOADING NORMALISATION

The spectral decomposition of the normalized Compromise matrix, designated as N_{ij}, is performed. From this decomposition, the initial eigenvector of the matrix V is selected, which corresponds to the set of coefficients $c = [c_1, c_2, \ldots, c_n]$. This normalization is achieved by dividing each coefficient by the sum of the absolute values of all the coefficients, calculated as follows:

$$S = \sum_{i=1}^{n} |c_i| \tag{28}$$

The normalization process ensures that the sum of the absolute values of the adjusted coefficients is equal to 1, a result that can be expressed mathematically as follows:

$$\sum_{i=1}^{n} |c_i^*| = 1 \tag{29}$$

2) FIBONACCI CATEGORIZED MATRIX

*Definition 6 (**Fibonacci categorized matrix**):* In evaluating the various financial indicators, J_k, the use of Fibonacci retracements is employed to categorize the observed trend according to its influence on the bank. If the indicator exerts a positive influence on the bank, it is classified as an uptrend in Equation (30). Conversely, if its impact is negative, it is classified as a downtrend in Equation (31).

Fibonacci Uptrend (A_4, E_1, L_2)

$$= \begin{cases} 5 & \text{si } 0.7861 \le x < 1.0000 \quad \text{(Excellent performance)} \\ 4 & \text{si } 0.6181 \le x < 0.7861 \quad \text{(Good performance)} \\ 3 & \text{si } 0.3821 \le x < 0.6181 \quad \text{(Stable)} \\ 2 & \text{si } 0.2361 \le x < 0.3821 \quad \text{(Risky performance} \\ 1 & \text{si } 0.0000 \le x < 0.2361 \quad \text{(Critical performance)} \end{cases} \tag{30}$$

Fibonacci Uptrend (C_3, M_2)

$$= \begin{cases} 1 & \text{si } 0.0000 \le x < 0.2361 \quad \text{(Critical performance)} \\ 2 & \text{si } 0.2361 \le x < 0.3821 \quad \text{(Risky performance)} \\ 3 & \text{si } 0.3821 \le x < 0.6181 \quad \text{(Stable)} \\ 4 & \text{si } 0.6181 \le x < 0.7861 \quad \text{(Good performance)} \\ 5 & \text{si } 0.7861 \le x \le 1.0000 \quad \text{(Excellent performance)} \end{cases} \tag{31}$$

Let Z_{t1} represent the time series of the first bank. Similarly, each subsequent bank is characterized by its own time series. To analyze the collective behavior of all banks in the Big segment, the above time series are consolidated into an overall data set. The consolidated time series for of segment B is given by the following:

$$\mathcal{Z}_B = \bigcup_{i=1}^{m} \{Z_{t_1(i)}, Z_{t_2(i)}, \ldots, Z_{t_n(i)}\} \tag{32}$$

In this context, m represents the total number of banks, while n denotes the length of the time series for each individual bank. The global data set Z_B allows for a comprehensive analysis of the observations of all banks in segment B. From Z_B, the global maximum and minimum values are defined as follows:

$$Z^{\max} = \max \mathcal{Z}_B = \max\{Z_{t_1}, Z_{t_2}, \ldots, Z_{t_{mn}}\} \tag{33}$$

$$Z^{\min} = \min \mathcal{Z}_B = \min\{Z_{t_1}, Z_{t_2}, \ldots, Z_{t_{mn}}\} \tag{34}$$

Once the maximum and minimum values of each J_k indicator have been determined, the Fibonacci levels observed in all time series can be identified. This methodology allows for the application of Fibonacci retracements to monitor the performance of the J_K financial indicator in the different phases: T_1 (pre-pandemic), T_2 (pandemic), and T_3 (Russia-Ukraine war). This facilitates the analysis of J_K financial indicator trends within the B segment, providing more detailed monitoring at each stage of the evaluated period.

3) WEIGHTED MATRIX W

The relationship between the vector of weights $\boldsymbol{\rho} = [\alpha_1, \alpha_2, \ldots, \alpha_5]$ (factor loadings) and the Categorized Fibonacci Matrix $\boldsymbol{F}_{ij}$, allows for the formulation of the Weighted Performance Matrix, denoted as $\boldsymbol{W}$. This matrix is obtained by multiplying each element of the vector of weights $\boldsymbol{\rho}$, by the corresponding column within $\boldsymbol{F}_{ij}$. Specifically, the first weight α_1 is applied to the first column of $\boldsymbol{F}_{ij}$, the second weight α_2 to the second column, and so on. This ensures that each column of $\boldsymbol{F}_{ij}$ is adjusted proportionally by its respective weight of $\boldsymbol{\rho}$.

$$\boldsymbol{W} = \begin{pmatrix} \alpha_1 F_{11} & \alpha_2 F_{12} & \alpha_3 F_{13} & \alpha_4 F_{14} & \alpha_5 F_{15} \\ \alpha_1 F_{21} & \alpha_2 F_{22} & \alpha_3 F_{23} & \alpha_4 F_{24} & \alpha_5 F_{25} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \alpha_1 F_{i1} & \alpha_2 F_{i2} & \alpha_3 F_{i3} & \alpha_4 F_{i4} & \alpha_5 F_{i5} \end{pmatrix} \tag{35}$$

4) BANK SCORE

The weighted matrix $\boldsymbol{W}$ was employed to perform row-wise summation calculations, thereby obtaining the total scores for each bank. Subsequently, these values were normalized in order to establish a bank ranking system. Subsequent calculations involved row-wise summations to derive total scores, which were then scaled to establish a banking ranking system. This method's distinct advantage over others lies in its ability to visually represent the classification component at the level of each indicator, incorporating the significance of the factor loadings for each indicator.

TABLE 2. Banking concentration in ecuador segment B (millions of dollars).

Bank	Segment	Assets	% Share	% Cumulative
Pichincha	B	15,465	29.08	29.08
Produbanco	B	6,994	13.15	42.23
Pacífico	B	6,990	13.14	55.37
Guayaquil	B	6,887	12.95	68.32
Internacional	B	4,605	8.66	76.98
Bolivariano	B	4,594	8.64	85.62
Others		7,656	14.39	100.00
TOTAL		53,191	100.00	

Source: Superintendencia de Bancos.
Note: Segment B refers to major banking institutions in Ecuador.

V. RESULTS

This section presents a review of the outcomes of the CAMEL partial triadic analysis (CPTA) model in relation to Ecuador's segment B banks.

A. BANKING CONCENTRATION IN ECUADOR

Table 2 illustrates the distribution of assets within the segment B banking sector of Ecuador. In particular, financial institutions such as Pichincha, Pacîfico, Produbanco, gauaquil, internacional y bolvariano hold market shares ranging from 29.08%, 13.15%, 13.14%, and 12.95%, respectively. This segment represents 34% of the total Ecuadorian banking market, thereby underscoring its significant role within the financial system.

B. VALIDATION OF VARIABLES FOR CAMEL PARTIAL TRIADIC MODEL

Each period, T_i aggregating 48 samples or observations for each indicator J_k, underwent the following statistical tests:

1) NORMALITY OF VARIABLES

Table 3 presents the Shapiro-Wilk test results for the financial indicators J_k over the periods T_i. Variables C_2, C_3, C_4, A_4, M_2, E_1, E_2, L_1, and L_2, highlighted in gray with p-values above 5%, confirm the null hypothesis H_0, indicating a normal distribution of data.

2) LEVENE'S TEST FOR EQUALITY OF VARIANCES

Table [4] details Levene's test presents the results of Levene's Test, assessing the equality of variances across different periods T_i for various financial indicators. Variable C_1, C_3, C_4, A_1, A_4, M_1, M_2, E_1, L_1, and L_2, which are highlighted in gray, exhibit p-values greater than 0.05, confirming homogeneity of variances across these groups. Conversely, variables C_2, A_2, A_3, M_3, and E_2 have p-values less than 0.05, indicating significant variances that suggest heterogeneity among these groups.

3) ONE-WAY ANOVA

The one-way ANOVA test, shown in Table [5], evaluates the null hypothesis H_0,which proposes that the means across different periods T_i are equal. Gray-highlighted variables C_3,

TABLE 3. Shapiro-Wilk test normality for periods.

BIG									
Indicator	Period	F-Statistic	Df	P-Value	Indicator	Period	F-Statistic	Df	P-Value
C_1	Pre-pandemic	0.930	48	0.007	C_2	Pre-pandemic	0.919	48	0.002
	Pandemic	0.891	48	0.000		Pandemic	0.982	48	0.643
	War	0.919	48	0.003		War	0.968	48	0.214
C_3	Pre-pandemic	0.975	48	0.384	C_4	Pre-pandemic	0.977	48	0.465
	Pandemic	0.981	48	0.633		Pandemic	0.981	48	0.604
	War	0.958	48	0.082		War	0.957	48	0.076
A_1	Pre-pandemic	0.632	48	0.000	A_2	Pre-pandemic	0.959	48	0.092
	Pandemic	0.703	48	0.000		Pandemic	0.807	48	0.000
	War	0.737	48	0.000		War	0.919	48	0.003
A_3	Pre-pandemic	0.932	48	0.008	A_4	Pre-pandemic	0.964	48	0.147
	Pandemic	0.948	48	0.033		Pandemic	0.969	48	0.230
	War	0.903	48	0.001		War	0.960	48	0.104
M_1	Pre-pandemic	0.948	48	0.032	M_2	Pre-pandemic	0.956	48	0.071
	Pandemic	0.953	48	0.053		Pandemic	0.976	48	0.432
	War	0.950	48	0.041		War	0.961	48	0.109
M_3	Pre-pandemic	0.879	48	0.000	E_1	Pre-pandemic	0.901	48	0.001
	Pandemic	0.966	48	0.176		Pandemic	0.965	48	0.161
	War	0.801	48	0.000		War	0.967	48	0.190
E_2	Pre-pandemic	0.983	48	0.714	L_1	Pre-pandemic	0.950	48	0.040
	Pandemic	0.962	48	0.121		Pandemic	0.982	48	0.679
	War	0.964	48	0.146		War	0.969	48	0.236
L_2	Pre-pandemic	0.982	48	0.662					
	Pandemic	0.972	48	0.293					
	War	0.96o4	48	0.102					

Note: The presented P-values indicate that the null hypothesis of a normal distribution of the variables in each quarter is not rejected and are above the significance threshold of 0.05.

TABLE 4. Levene's test for equality of variances.

BIG BANK				
Measure	Levene Statistic	d_{f1}	d_{f2}	$P\text{-}Value$
C_1	1.606	2	141	0.204
C_2	3.586	2	141	0.030
C_3	0.760	2	141	0.204
C_4	2.074	2	141	0.129
A_1	1.670	2	141	0.192
A_2	7.910	2	141	0.001
A_3	7.450	2	141	0.001
A_4	0.986	2	141	0.375
M_1	1.732	2	141	0.181
M_2	0.679	2	141	0.509
M_3	4.630	2	141	0.011
E_1	0.001	2	141	0.999
E_2	4.246	2	141	0.016
L_1	1.518	2	141	0.208
L_2	1.318	2	141	0.271

Note: P-values exceeding the significance threshold of 0.05 suggest the null hypothesis H_0 of homogeneity of variance-covariance matrices is not rejected for the highlighted variables.

TABLE 5. One-way ANOVA.

BIG					
Indicator	Sum of Squares	Df	Mean Square	F-Statistic	P-Value
C_1	18.136	2	9.068	3.760	0.260
C_2	0.575	2	0.288	0.623	0.538
C_3	21253.612	2	10626.806	9.929	0.000
C_4	5.309	2	2.654	2.015	0.137
A_1	14.420	2	7.210	537	0.586
A_2	11853.429	2	5926.714	32.302	0.000
A_3	44020	2	2200.417	1.789	0.171
A_4	576.319	2	288.159	25.012	0.000
M_1	3949.375	2	1974.688	8.609	0.000
M_2	17.175	2	8.587	15.437	0.000
M_3	1.816	2	0.933	22.221	0.000
E_1	13.445	2	6.722	94.139	0.000
E_2	1272.384	2	636.1912	102.813	0.000
L_1	321.992	2	160.192	5.092	0.007
L_2	846.164	2	423.082	16.615	0.000

Note: The P-values presented are below the significance level of 0.05, indicating that the null hypothesis of equal means across periods is rejected. Therefore, these indicators detect differences between periods.

$A_3, A_4, M_1, M_3, E_1, E_2, L_1$, and L_2 indicate p-values above the significance level (0.05), thus supporting the hypothesis of equal means across periods. Conversely, C_1, C_2, C_4, A_1, and A_3 demonstrate p-values below 0.05, suggesting significant differences in their means across periods, which refutes H_0.

4) JUSTIFICATION FOR THE SELECTION OF PERIODS T_I

Initially, the Shapiro-Wilk test and the Levene's test were applied to validate the normality and homogeneity of variances, respectively. These preliminary tests are essential to ensure the applicability of the one-factor ANOVA, which was subsequently used to examine the differences among the periods T_i in relation to the selected variables.

The statistical analysis revealed significant differences in the variables C_3, A_4, M_2, E_1 and L_2. The results indicate that the periods T_1, T_2 and T_3, which represent specific quarters within T_i, are crucial for assessing the impacts of two disruptive events: the COVID-19 pandemic and the

TABLE 6. Indices finance of model camels.

Ind.	Formulas $q_1, \ldots, q_3$	Formulas q_4	Impact
C_3	$\frac{Capital}{total\ Assets}$	$\frac{Capital}{total\ Assets}$	-
A_4	$\frac{Productive\ assests}{Total\ assets}$	$\frac{productive\ Assests}{total\ Assets}$	+
M_2	$\frac{\frac{Operating\ personal \times 12}{number\ of\ moths}}{averange\ Assets}$	$\frac{Operating\ personal}{total\ Assets}$	-
E_1	$\frac{\frac{Operating\ expenses \times 12}{number\ of\ moths}}{averange\ Assets}$	$\frac{Operating\ expenses}{total\ Assets}$	+
L_2	$\frac{Liquid\ assets\ at\ 90}{Obligations\ with\ the\ public}$	$\frac{Liquid\ assets\ at\ 90}{Obligations\ with\ the\ ppublic}$	+

Note: Formulas for K_1 to k_3 are used for standard quarterly analysis; K_4 formulas account for year-end adjustments in December closing.

Russia-Ukraine war, on financial indicators in Ecuadorian banks in segment B.

The choice of these intervals to apply the CAMEL Partial Triadic Analysis (CPTA) is directly aligned with the research objectives, allowing a detailed exploration of the effects of these crises on critical financial indicators impacted by the adversities faced by the Ecuadorian banking sector.

C. INTER-STRUCTURE

In our study, we analyzed interactions between matrix pairs S_k y S'_k, through the cross product to determine the vector covariance. This method enabled examination of similarities among matrices from different quarters k within each period T_i. Subsequently, we implemented the generalized Hilbert-Schmidt Equation (15), which facilitated the creation of the correlation matrix R_v. This matrix encapsulated all correlations between the analyzed vectors, revealing patterns followed by the matrices $\mathbf{X}_k$ throughout the period T_i.

1) EVOLUTIVE ANALYSIS OF INTER-QUARTER CORRELATIONS

Periodos	Mar_2018	Jun_2018	Sep_2018	Dec_2018	Mar_2019	Jun_2019	Sep_2019	Dec_2019
Mar_2018	1.0000	0.9180	0.9317	0.8483	0.8760	0.8231	0.7845	0.7565
Jun_2018	0.9180	1.0000	0.9205	0.8657	0.8847	0.8034	0.8644	0.8249
Sep_2018	0.9317	0.9205	1.0000	0.8954	0.8939	0.8307	0.7980	0.7733
Dec_2018	0.8483	0.8657	0.8954	1.0000	0.9074	0.8981	0.9069	0.9137
Mar_2019	0.8760	0.8847	0.8939	0.9074	1.0000	0.9274	0.9287	0.9109
Jun_2019	0.8231	0.8034	0.8307	0.8981	0.9274	1.0000	0.9200	0.8961
Sep_2019	0.7845	0.8644	0.7980	0.9069	0.9287	0.9200	1.0000	0.9714
Dec_2019	0.7565	0.8249	0.7733	0.9137	0.9109	0.8961	0.9714	1.0000

FIGURE 7. Correlation pre-pandemic.

- **Prepandemic Period (T_1):** Figure 7 depicts the evolution of inter-quarter correlations during the pre-pandemic period. Prior to the pandemic, the analysis of inter-quarter correlations revealed a gradual decline, indicating a weakening of systemic financial stability. In 2018, the correlation between quarters exhibited fluctuations, beginning at $R_{12} = 0.9180$ from March to June and then showing a slight increase to $R_{24} = 0.9205$ from June to September. However, it subsequently decreased to $R_{35} = 0.8954$ from September to December.
- This declining trend continued into 2019, with the correlation decreasing further to $R_{75} = 0.9074$ from December 2018 to March 2019 and then to $R_{56} = 0.9274$ from March 2019 to June 2019. Subsequent evaluations indicated that volatility persisted, as evidenced by the correlation coefficients $R_{67} = 0.9200$ from June to September 2019 and $R_{78} = 0.9714$ from September to December 2019.

Periodos	Mar_2020	Jun_2020	Sep_2020	Dec_2020	Mar_2021	Jun_2021	Sep_2021	Dec_2021
Mar_2020	1.0000	0.8525	0.6749	0.4996	0.3970	0.3203	0.5320	0.4259
Jun_2020	0.8525	1.0000	0.8157	0.7395	0.5288	0.5046	0.5804	0.4912
Sep_2020	0.6749	0.8157	1.0000	0.7544	0.7195	0.4651	0.5727	0.4651
Dec_2020	0.4996	0.7395	0.7544	1.0000	0.8209	0.8094	0.6140	0.5807
Mar_2021	0.3970	0.5288	0.7195	0.8209	1.0000	0.8559	0.7815	0.7286
Jun_2021	0.3203	0.5046	0.4651	0.8094	0.8559	1.0000	0.7990	0.7714
Sep_2021	0.5320	0.5804	0.5727	0.6140	0.7815	0.7990	1.0000	0.9447
Dec_2021	0.4259	0.4912	0.4651	0.5807	0.7286	0.7714	0.9447	1.0000

FIGURE 8. Correlation pandemic.

- **Pandemic period (T_2):** Figure 8 illustrates the evolution of inter-quarter correlations during the period of the pandemic. In the initial phase of the pandemic in 2020, an examination of inter-quarter correlations indicated considerable variability, indicative of systemic disruptions. The correlation commenced at $R_{12} = 1.0000$ in March 2020, signifying a perfect self-correlation. By June 2020, this correlation with March had decreased to $R_{12} = 0.8525$, indicating the initial impact of the pandemic-induced economic stress. The decline persisted, with correlations declining to $R_{13} = 0.6749$ from March to September and subsequently to $R_{14} = 0.4996$ by December 2020.
- In 2021, the data indicate the persistence of instability, with mixed trends. From December 2020 to March 2021, the correlation exhibited a slight recovery, reaching $R_{15} = 0.3970$. However, it subsequently declined to $R_{16} = 0.3203$ from March to June 2021. This represented the nadir of inter-quarter correlations during the pandemic period. Towards the latter half of 2021, a modest recovery was observed, with correlations rising to $R_{17} = 0.5320$ by September 2021 and stabilizing at $R_{18} = 0.4259$ by December 2021. These fluctuations are indicative of the prolonged volatility and the uneven adjustment of the financial sector during the pandemic.

Periodos	Mar_2022	Jun_2022	Sep_2022	Dec_2022	Mar_2023	Jun_2023	Sep_2023	Dec_2023
Mar_2022	1.0000	0.9407	0.9634	0.8677	0.8289	0.8974	0.8047	0.6432
Jun_2022	0.9407	1.0000	0.9716	0.8783	0.8366	0.9049	0.8046	0.5877
Sep_2022	0.9634	0.9716	1.0000	0.9216	0.8486	0.9003	0.7945	0.6538
Dec_2022	0.8677	0.8783	0.9216	1.0000	0.9160	0.9037	0.8441	0.7812
Mar_2023	0.8289	0.8366	0.8486	0.9160	1.0000	0.9511	0.8961	0.7318
Jun_2023	0.8974	0.9049	0.9003	0.9037	0.9511	1.0000	0.9380	0.7318
Sep_2023	0.8047	0.8046	0.7945	0.8441	0.8961	0.9380	1.0000	0.7885
Dec_2023	0.6432	0.5877	0.6538	0.7812	0.7318	0.7318	0.7885	1.0000

FIGURE 9. Correlation War Russia-Uckraine.

- **War Russia-Uckraine period (T_3):** Figure 9 illustrates the evolution of inter-quarter correlations during the period of the pandemic. In the initial phase of the pandemic in 2020, an examination of inter-quarter correlations indicated considerable variability, indicative of systemic disruptions. The correlation commenced at

$R_{12} = 1.0000$ in March 2020, signifying a perfect self-correlation. By June 2020, this correlation with March had decreased to $R_{12} = 0.8525$, indicating the initial impact of the pandemic-induced economic stress. The decline persisted, with correlations declining to $R_{13} = 0.6749$ from March to September and subsequently to $R_{14} = 0.4996$ by December 2020.

- In 2021, the data indicate the persistence of instability, with mixed trends. From December 2020 to March 2021, the correlation exhibited a slight recovery, reaching $R_{15} = 0.3970$. However, it subsequently declined to $R_{16} = 0.3203$ from March to June 2021. This represented the nadir of inter-quarter correlations during the pandemic period. Towards the latter half of 2021, a modest recovery was observed, with correlations rising to R17 = 0.5320 by September 2021 and stabilizing at R18 = 0.4259 by December 2021. These fluctuations are indicative of the prolonged volatility and the uneven adjustment of the financial sector during the pandemic.

2) PCA OF MATRIZ R_V

Utilizing Equation (18), for the eigenvalue decomposition of matrix R_v, we conducted a Principal Component Analysis (PCA). This analysis focused on the first two principal axes to simplify data representation and highlight similarities among the eight matrices corresponding to each quarter within periods T_i. The projection of vectors $\boldsymbol{S}_k$, onto these axes allowed us to:

- Identify common structures across all matrices, focusing on significant patterns and differences throughout the period T_i among the datasets $\boldsymbol{X}_k$.
- Investigate the significance of outliers, emphasizing those whose contributions to squared distances markedly deviated from the norm.

This section presents the principal findings of the Principal Component Analysis (PCA), with a focus on the correlation between various vectors and the primary component. The results are organized by relevant periods, designated as T_i:

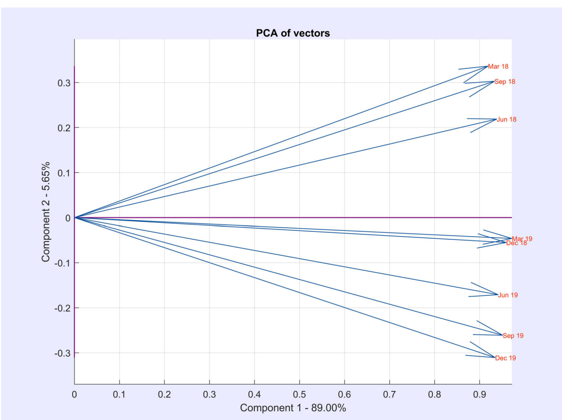


FIGURE 10. **PCA Prepandemic.**

Pre-Pandemic (T_1): As depicted in Figure 10, the primary component accounted for 89.00% of the variability, while the secondary component captured 5.65%. We identified three vector groups:

- $G_{T_{11}}$: Includes the quarters *Marzo* $_{2018}$, *June* $_{2018}$ and *Septiembre* 2018, with angles of 20.12°, 13.14° and 17.99° respectively.
- $G_{T_{12}}$: Comprises the quarters *December*$_{2018}$ and *March*$_{2019}$, with angles of $-3.29°$ and $-2.720°$ respectively.
- $G_{T_{13}}$: Consists of the quarters *June*$_{2019}$, *September*$_{2019}$ and *December*$_{2019}$, with angles of $-10.303°$, $-15.35°$ and $-18.39°$.

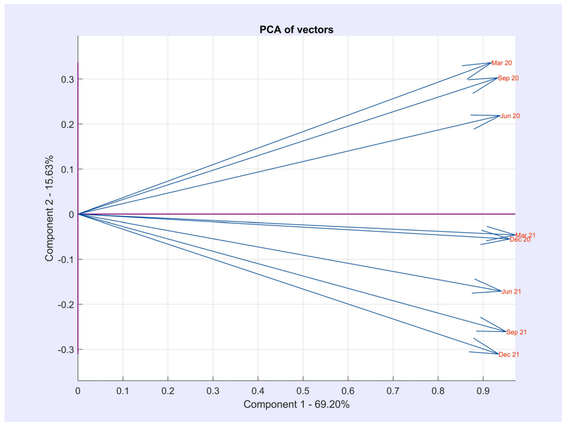


FIGURE 11. **PCA Pandemic.**

Pandemic (T_2): According to Figure 11, the primary component explained 69.20% of the variability, and the secondary component captured 15.63%. A primary vector group was identified:

- $G_{T_{21}}$: Includes the quarters *March*$_{2020}$, *June*$_{2020}$ and *September*$_{2020}$, with angles of 40.77°, 31.90° and 25.49° respectively.
- $G_{T_{22}}$: Includes the quarters *March*$_{2021}$ and *September*$_{2021}$, with angles of $-16.81°$ and $-17.70°$ respectively.
- $G_{T_{23}}$: Includes the quarters *June*$_{2021}$ and *December*$_{2021}$, with angles of $-27.02°$ and $-25.20°$ respectively.

War Russia-Ukraine (T_3): As indicated in Figure 12, the primary component captured 86.31% of the variability,and the secondary component accounted for 7.11%. Two vector groups were identified:

- $G_{T_{31}}$:Includes the quarters *March*$_{2022}$ and *September*$_{2022}$ with angles of 14.47° and 14.47° respectively.

3) GLOBAL ANALYSIS INTEGRATING ALL QUARTERS K WITHIN THE PERIOD T_I

Figure 13 depicts the integration of the temporal data corresponding to the three distinct epochs along a single factorial axis. This allows for an evolutionary comparison of the periods in question. This approach, which employs a particular instance of biplot methodology, is designated

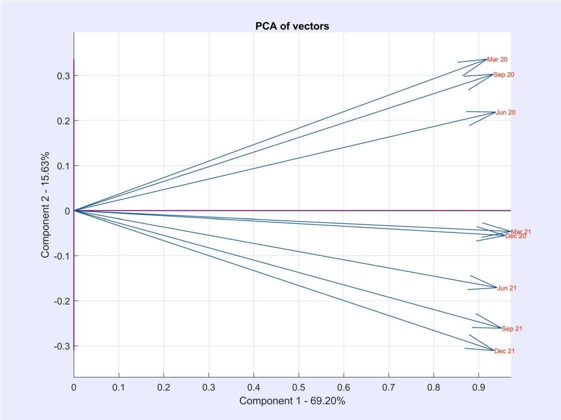


FIGURE 12. PCA war russia-ukraine.

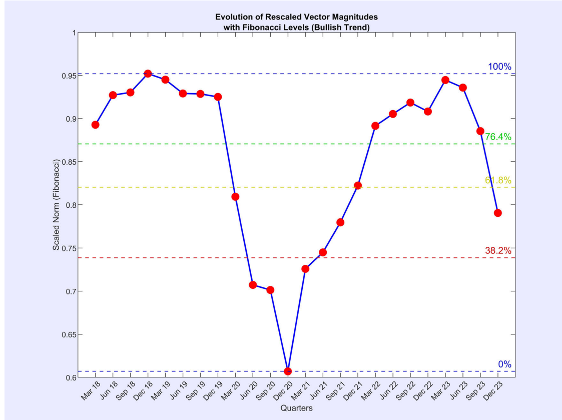


FIGURE 14. Evolution of global norms.

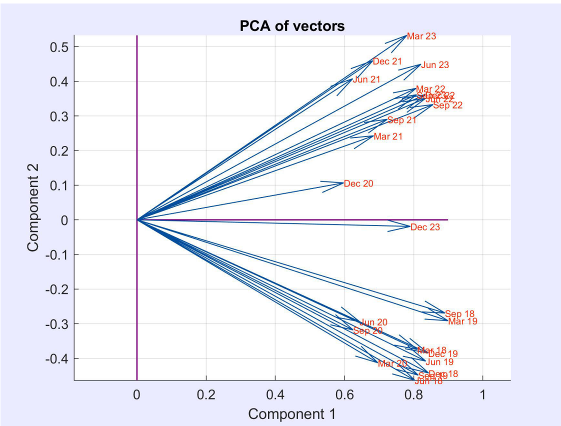


FIGURE 13. PCA Global.

as the Dynamic Biplot. The periods under comparison are: T_1 (pre-pandemic), T_2 (pandemic), and T_3 (War Russian-Ukraine). This provides a representation of the changes in the J_k financial indicators between the analyzed periods.

4) ANALYSIS OF THE EVOLUTION OF NORMS ACROSS ALL QUARTERS K WITHIN THE PERIOD T_l

Figure 14 the banking sector operates in a highly dynamic environment, shaped by a complex interplay of macroeconomic and geopolitical forces. In particular, recent events such as the 2020-2021 pandemic caused by the novel coronavirus (Covid-19) and the 2022-2023 Russia-Ukraine conflict have posed considerable challenges to the stability of financial indicators. Figure 23 illustrates the evolution of vector norms over k quarters, allowing for a detailed observation of fluctuations in critical periods.

- **Prepandemic Period (T_1):** From the first quarter of 2020 onward, the observed values began to decline. In March 2020, which marks the onset of the global pandemic caused by the novel coronavirus, the norm reaches a value of 0.8093. This decline persists in June and September 2020, with respective values of 0.7073 and 0.7013. The decline becomes more pronounced towards December 2020, when the norm reaches its lowest point at 0.6070. This reflects high instability and chaos in the financial dynamics, affecting the vectorized matrices and demonstrating the impact of the pandemic on the Ecuadorian financial market.
- **Pandemic Period (T_2):** The initial decline in norms is observed from the first quarter of 2020 onwards. In March 2020, which marks the onset of the global pandemic caused by the novel coronavirus, the norm reaches a value of 0.8093. This decline persists in June and September of the same year, with respective values of 0.7073 and 0.7013. The decline becomes increasingly pronounced as we move towards December 2020, when the norm reaches its lowest point at 0.6070. This reflects a considerable degree of instability and chaos in the financial dynamics, which are affecting the vectorized matrices and demonstrating the impact of the pandemic on the Ecuadorian financial market. However, a gradual recovery is observed as of 2021. In March 2021, the norm exhibited an increase, reaching a value of 0.7259. This occurred concurrently with the commencement of vaccination campaigns and the gradual lifting of restrictions imposed due to the global pandemic caused by the SARS-CoV-2 virus. The recovery process continued in June and September of 2021, with norms reaching values of 0.7450 and 0.7797, respectively. In December 2021, the norm increased to 0.8223, approaching pre-pandemic levels. This reflected a progressive recovery of financial stability, aligned with the relaxation of restrictions and the adaptation of the economic system to the new normality.
- **War Russia-Uckraine (T_3):** The data for the year 2022 demonstrates a relatively consistent pattern, commencing in March 2021 with a value of 0.8915 and culminating in December 2022 with a value of 0.9082. This indicates that, despite the conflict between Russia and Ukraine, the Ecuadorian financial market was not significantly impacted during its initial stages. Nevertheless, a definitive return to the levels observed

TABLE 7. Tables weights α_k in the Compromise's for period.

Quaters T_1	α_k	Quaters T_2	α_k	Quaters T_3	α_k
Mar_{2018}	0.3143	Mar_{2020}	0.2933	Mar_{2022}	0.3571
Jun_{2018}	0.3515	Jun_{2020}	0.3481	Jun_{2022}	0.3564
Sep_{2018}	0.3496	Sep_{2020}	0.3474	Sep_{2022}	0.3627
Dec_{2018}	0.3594	Dec_{2020}	0.3743	Dec_{2022}	0.3647
Mar_{2019}	0.3641	Mar_{2021}	0.3771	Mar_{2023}	0.3597
Jun_{2019}	0.3526	Jun_{2021}	0.3582	Jun_{2023}	0.3710
Sep_{2019}	0.3564	Sep_{2021}	0.3741	Sep_{2023}	0.3518
Dec_{2019}	0.3901	Dec_{2021}	0.3482	Dec_{2023}	0.3003

prior to the pandemic has yet to occur. However, a slight increase followed by a subsequent decrease is observed throughout 2023. In March 2023, the norm reached a value of 0.9447, then declined in September and December 2023 to 0.8854 and 0.7905, respectively. This fluctuation suggests the advent of a new phase of uncertainty, precipitated by the intensifying conflict between Russia and Ukraine. This has resulted in elevated energy prices, global inflation, rising interest rates by the U.S. Federal Reserve, and higher freight costs due to geopolitical tensions. The decline in standards towards the end of 2023 indicates a widening dispersion of financial data, reflecting the increasing variability of the country's financial indicators.

D. INTRA-STRUCTURE

1) COMPROMISE MATRIX FOR PERIOD

Initially, we determined the weights for an optimal representation of the data matrix set $\boldsymbol{X}_k$ during the period T_i [50]. This process was accomplished through spectral decomposition of the Matrix Compromise $\boldsymbol{C}_{ij}$, applying Equation (21). This procedure enabled us to isolate the principal eigenvector, which contains the weights applicable to the matrices $\boldsymbol{X}_k$; we have referred to these weights as αk. Table 7 lists these weights for the periods T_i.

Using these weights, we applied Equation (22) to each of the matrices $\boldsymbol{X}_k$. This resulted in the Compromise matrix $\boldsymbol{C}ij$, containing original data, as detailed in Table 9 for the periods T_i. The values within these matrices exhibit changes in the financial indicators of each bank. This observation broadly highlights the impacts of the COVID-19 pandemic and the Russia-Ukraine wart on banking performance.

2) COMPROMISE MATRIX FOR DYNAMIC BIPLOT

In our approach, the commitment matrix was obtained by aggregating the $\boldsymbol{X}_k$ Compromise matrix matrices of the three periods (T_1) prepademci, (T_2) pandemic and (T_3) Russian-Ukrainian war and applying spectral. The result of one of the weights was weighted by the observation period method.

E. HJ-BIPLOT

This study examined the interactions between banks I_K and financial indicators J_k over periods T_i using the HJ-Biplot technique. After employing Singular Value Decomposition (SVD) on the Compromise matrix $\boldsymbol{C}_{ij}$, we proceeded with

TABLE 8. Tables weights α_k for the compromise matrix across all quaters k.

Quaters T_1	α_k	Quaters T_2	α_k	Quaters T_3	α_k
Mar_{2018}	0.2128	Mar_{2020}	0.1828	Mar_{2022}	0.2118
Jun_{2018}	0.2108	Jun_{2020}	0.1689	Jun_{2022}	0.2191
Sep_{2018}	0.2338	Sep_{2020}	0.1641	Sep_{2022}	0.2248
Dec_{2018}	0.2214	Dec_{2020}	0.1569	Dec_{2022}	0.2155
Mar_{2019}	0.2361	Mar_{2021}	0.1796	Mar_{2023}	0.2188
Jun_{2019}	0.2192	Jun_{2021}	0.1637	Jun_{2023}	0.2048
Sep_{2019}	0.2135	Sep_{2021}	0.1900	Sep_{2023}	0.2122
Dec_{2019}	0.2209	Dec_{2021}	0.1790	Dec_{2023}	0.2075

the HJ-Biplot. Our analysis enabled the optimal selection of markers $H_i = (h_1, h_2, \ldots, h_q)$ for rows and $J_j = (j_1, j_2, \ldots, j_q)$ for columns, aligning them with the factorial coordinates of the designated axes. The orthogonal projection of rows and columns preserved the total variance Λ, through the orthogonality of matrices U and V as discussed in Section V-D.

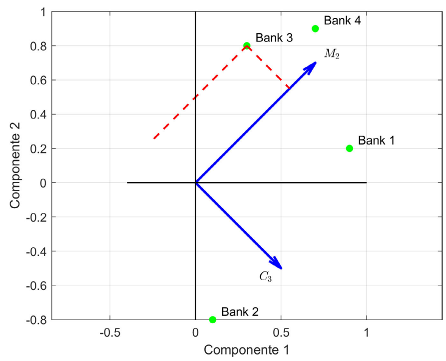


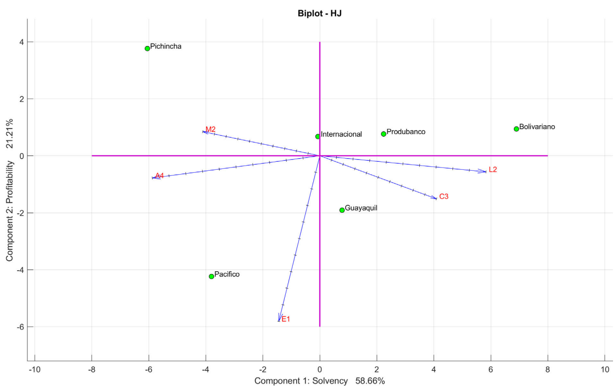
FIGURE 15. BIPLOT.

The HJ-Biplot is a technique where all vectors emerge from a common initial point, revealing both the direction and magnitude that characterize each indicator's contribution to the total variability. By positioning each bank relative to these vectors, we assessed their relative performance: those positioned in the direction and sense of the vector demonstrated superior performance to the group average, represented by μ, within their banking sector. Conversely, positioning in the opposite direction indicated below-average performance.

1) HJ-BIPLOT ANALYSIS OF PERIOD T_1

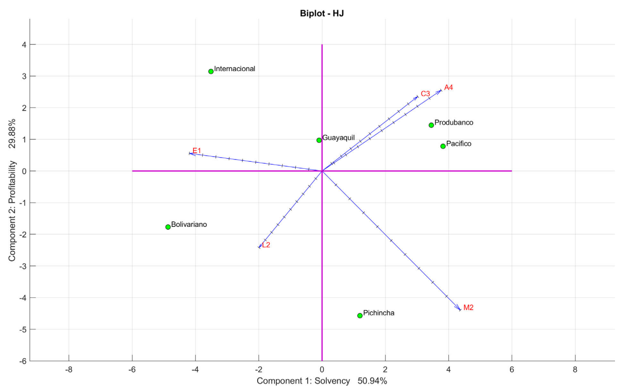
Figure 16 the HJ-Biplot plot for the pre-pandemic period. The analysis shows that the first principal component explains 39.45% of the variability, while the second principal component explains 21.21%. Together, these two components capture a significant proportion of the variability in the data, totalling 79.87%.

- The correlation between the Gross loans/Assets ratio (A_4) and the personal efficiency ratio (M_2) is as follows: The vectors are relatively long and form a small angle to each other, indicating a strong positive correlation.



μ	C_3	A_4	M_2	E_1	L_2	Correlation	Angles	Degree
Pichincha	←	←	→	←	←	Yes	E_1 and A_2	9.30 °
Pacifico	←	→	→	→	←	Yes	C_3 and L_2	11.80 °
Guayaquil	→	→	←	→	→	Inverse	M_2 and C_3	170.40 °
Produbanco	→	→	←	=	=	No	M_2 and C_3	82.10 °
Internacional	←	→	=	→	→			
Bolivariano	→	←	←	←	→			

FIGURE 16. HJ-Biplot - Prepandemic T_1.



μ	C_3	A_4	M_2	E_1	L_2	Correlation	Angles	Degree
Pichincha	←	←	→	→	→	Yes	L_2 and E_1	29.30 °
Pacifico	→	→	→	←	←	Yes	C_3 and A_2	40.40 °
Guayaquil	→	→	←	→	←			
Produbanco	→	→	→	←	←			
Internacional	←	→	←	→	→			
Bolivariano	←	=	←	→	→			

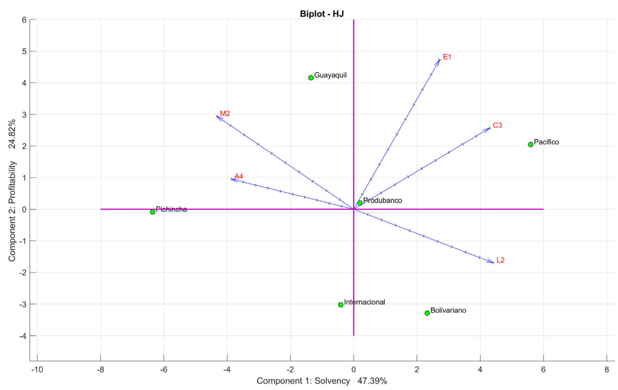
FIGURE 17. HJ-Biplot - Pandemic T_2.

- The correlation between the ratio of Net non-performing assets/assets (C_3) and adjusted liquidity (L_2) is as follows: The vectors in question are also of considerable length, but their opposite direction indicates a negative correlation.

2) HJ-BIPLOT ANALYSIS OF PERIOD T_2

Figure 17: The Hj-Biplot illustrates of the pandemic. The first principal component accounts for 50.94% of the total variability, while the second principal component accounts for 29.88%.

- The correlation between the net non-performing assets ratio (C_3) and the gross loans/assets ratio (A_4) is as follows: the vectors demonstrated considerable variability and a high degree of correlation.
- The correlation between the Personal Efficiency Ratio (M_2) and the Gross Loans/Assets Ratio (A_4) is as follows: The length of these vectors remains significant and the positive correlation persists.



μ	C_3	A_4	M_2	E_1	L_2	Correlation	Angles	Degree
Pichincha	←	←	→	←	←	Yes	E_1 and A_2	9.30 °
Pacifico	←	←	→	→	←	Yes	C_3 and L_2	11.80 °
Guayaquil	→	→	←	→	→	Inverse	M_2 and C_3	170.40 °
Produbanco	→	→	←	=	=	No	M_2 and C_3	82.10 °
Internacional	←	→	=	→	→			
Bolivariano	→	←	←	←	→			

FIGURE 18. HJ-Biplot - War Russia-Ucranine T_3.

3) HJ-BIPLOT ANALYSIS OF PERIOD T_3

Figure 18: The Hj-Biplot illustrates of the pandemic. The first principal component accounts for 47.39% of the total variability, while the second principal component accounts for 24.82%.

- The correlation between the Personal Efficiency Ratio (M_2) and the Gross Loans/Assets Ratio (A_4) is as follows: The length of these vectors remains significant and the positive correlation persists.

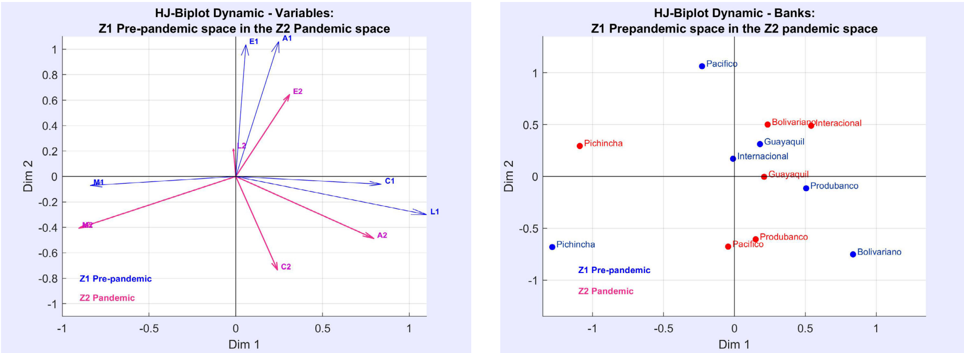
F. BIPLOT DYNAMIC

1) THE TRANSITION FROM THE PRE-PANDEMIC PERIOD T_1 TO THE PANDEMIC PERIOD T_2

The ongoing pandemic has had a significant impact on the banking sector, particularly in regard to operational efficiency and liquidity management. In order to gain a deeper comprehension of these alterations, a Dynamic HJ-Biplot representation is utilized. In this analysis, Z_1 represents the projection of the variables in the dynamic HJ-Biplot corresponding to the pre-pandemic period (T_1), Z_2 represents the variables during the pandemic period (T_2), and Z_3 corresponds to the variables associated with the period of the Russia-Ukraine conflict (T_3). The observations for each bank are detailed below:

- **Pichincha**
  The delinquency indicator exhibited an 18.69% increase, indicative of a rise in the volume of non-performing assets during the pandemic. Notwithstanding this challenge, there was an increase of 61.2% in adjusted liquidity, which is indicative of an enhanced

TABLE 9. Evolution of the compromise matrix between periods T_1 y T_2.



Banks	T_1 Pre-pandemic C_3	A_4	M_2	E_1	L_2	T_2 Pandemic C_3	A_4	M_2	E_1	L_2
Pichincha	115.5701	53.9591	5.6111	1.1122	19.4626	137.1719	46.8063	4.9605	0.6437	31.3745
Pacifico	138.6664	62.9991	4.6040	1.8092	23.3369	187.0525	57.3685	4.1516	0.4403	31.1767
Guayaquil	154.0920	59.8924	4.6504	1.5419	28.6882	161.1380	57.4552	3.7358	0.7436	31.4635
Produbanco	170.6614	60.4210	4.3618	1.1205	30.1256	182.6963	58.9329	4.0413	0.5808	32.4644
Internacional	114.1245	60.4210	3.1396	1.3152	24.6134	145.5304	56.3884	2.8162	0.8699	29.2332
Bolivariano	165.1448	60.0784	3.6542	1.2111	34.8101	154.3162	55.0138	3.3507	0.8457	38.2140
Centroide	**143.0432**	**58.6630**	**4.3368**	**1.3667**	**26.8395**	**161.3175**	**55.3275**	**3.8427**	**0.6873**	**32.3211**

Bancos	T_2 - T_1 Variation C_3	A_4	M_2	E_1	L_2	T_2 - T_1 Growth C_3	A_4	M_2	E_1	L_2
Pichincha	21.6018	-7.1528	-0.6505	-0.4685	11.9191	18.69%	-13.26%	-11.59%	-42.13%	61.20%
Pacifico	48.3860	-5.6307	-0.4524	-1.3689	7.8398	34.89%	-8.94%	-9.83%	-75.66%	33.59%
Guayaquil	7.459	-2.4373	-0.9146	-0.7982	2.7753	4.57%	-4.07%	-19.67%	-51.77%	9.67%
Produbanco	12.0349	- 1.4881	-0.3205	-0.6297	2.3388	7.05%	-2.46%	-7.35%	-52,02%	7.76%
Internacional	31.4058	-3.6990	-0.3233	-0.4453	4.6198	27.52%	-6.16%	-10.30%	-33.86%	18.77%
Bolivariano	-10.8285	-0.3947	-0.3036	-0.3654	3.6198	-6.56%	0.72%	-8.31%	-30.17%	9.78%

C_3: Non-productive Assets / Equity
A_2: Gross Loans / Assets
M_2: Personnel Expenses / Operating Expenses
E_1: Return on Assets - ROA
L_2: Adjusted Liquidity

capacity for liquidity management during the period of the health crisis.

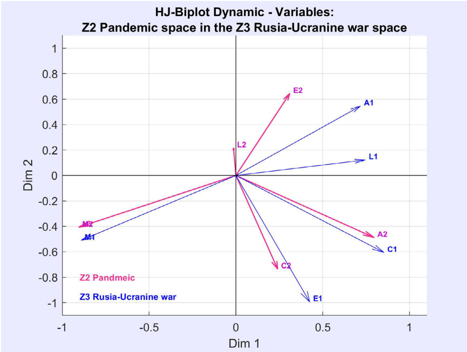
- **Pacifico**
  The non-performing loans indicator increased by 34.89%. Adjusted liquidity improved by 33.59%, demonstrating solid management of liquid assets.
- **Pacifico**
  Gross loans to assets increased by 4.57%. Adjusted liquidity grew 9.67%, indicating an improved ability to manage liquid assets.
- **Produbanco**
  There was a 7.05% increase in the return on assets. The adjusted liquidity ratio increased by 7.76%, which is indicative of an improvement in the management of liquid assets.
- **Banco Internacional**
  The growth in adjusted liquidity, at 9.78%, suggests an enhanced capacity to manage these assets.

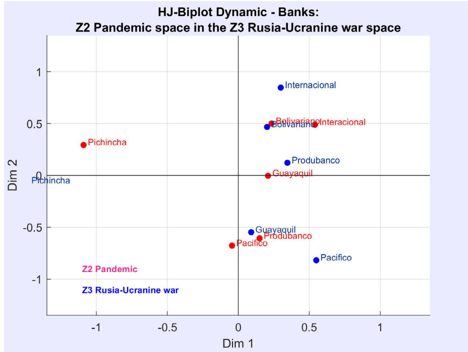
The analysis of the Ecuadorian banking sector during the pandemic reveals a behaviour pattern analogous to that observed in Southeast Asian countries, as previously highlighted by Ramli et al. [59]. In both instances, the prevailing uncertainty prompted an increase in liquidity, with individuals opting to maintain their funds in banking institutions rather than directing them towards consumption, thereby temporarily enhancing liquidity capacity.

2) THE TRANSITION FROM THE PANDEMIC PERIOD T_2 TO THE PANDEMIC WAR RUSSIA-UKRAINE T_3

- **Pichincha**
  The return on assets exhibited a 75.31% increase, indicative of augmented operational capacity and a discernible recuperation from the pandemic. However, adjusted liquidity decreased by 27.51%, indicating that the bank should reassess its strategy for managing liquid assets in the context of heightened volatility, which has been further exacerbated by the war in Eastern Europe.
- **Pacifico**
  Notwithstanding a slight decline in operating efficiency, with non-performing assets decreasing by 11.78%, the return on assets exhibited a notable increase of 267.36%. This suggests that the bank was able to reallocate its resources toward more lucrative investments during the transition from a pandemic to a geopolitical crisis. The stability of adjusted liquidity, with a minimal

TABLE 10. Evolution of the compromise matrix between periods T_1 y T_3.





Bancos	T_2 Pandemic					T_3 Russia-Ukraine War				
	C_3	A_4	M_2	E_1	L_2	C_3	A_4	M_2	E_1	L_2
Pichincha	137.1719	46.8063	4.9605	0.6437	31.3745	90.2649	53.2442	4.5923	1.1284	22.7448
Pacifico	187.0525	57.3685	4.1516	0.4403	31.1767	165.0096	55.5831	3.1203	1.6175	30.2211
Guayaquil	161.1380	57.4552	3.7358	0.7436	31.4635	139.8299	63.2897	3.7999	1.6167	23.4033
Produbanco	182.6963	58.9329	4.0413	0.5808	32.4644	154.2609	63.3426	3.9346	1.1357	26.3313
Internacional	145.5304	56.3884	2.8162	0.8699	29.2332	115.1123	64.0968	2.5660	1.1357	26.3313
Bolivariano	154.3162	55.0138	3.3507	0.8457	38.2140	116.9286	60.0816	2.9705	1.1996	30.1320
Centroide	**161.3175**	**55.3275**	**3.8427**	**0.6873**	**32.3211**	**130.2344**	**59.9337**	**3.4973**	**1.3056**	**27.2317**

Bancos	C_3	A_4	M_2	E_1	L_2	C_3	A_4	M_2	E_1	L_2
	T_2 - T_3 Variation					T_2 - T_3 Growth				
Pichincha	-46.9070	6.4379	-0.3682	0.4848	-8.6298	-34.20%	13.75%	-7.42%	75.31%	-27.51%
Pacifico	-22.0429	-1.7854	-1.0313	1.1772	-0.9556	-11.78%	-3.11%	-24.84%	267.36%	-3.06%
Guayaquil	-21.3081	5.8346	0.0642	0.8731	-8.0602	-13.22%	10.16%	1.72%	117.40%	-25.62%
Produbanco	-28.4354	4.4097	-0.1067	0.5550	- 1,9700	-15.56%	7.48%	-2.64%	95.55%	-5.87%
Internacional	-30.4180	7.7084	-0.2503	0.2658	-2.9019	-20.90%	13.67%	-8.89%	30.55%	-9.93%
Bolivariano	-37.3877	5.0677	-0.3802	0.3538	-8.0821	-24.23%	9.21%	-11.35%	41.84%	-21.15%

C_3: Non-productive Assets / Equity
A_2: Gross Loans / Assets
M_2: Personnel Expenses / Operating Expenses
E_1: Return on Assets - ROA
L_2: Adjusted Liquidity

decline of 3.06%, and a reduction in personnel expenses of 24.84%, demonstrate effective cost management without compromising overall responsiveness.

- **Guayaquil**
  The volume of gross loans exhibited an increase of 10.16%, which is indicative of the bank's augmented lending capacity. The return on assets increased by 117.40%, while adjusted liquidity decreased by 25.62%. This evidence suggests a vulnerability in the management of liquid assets.
- **Produbanco**
  The Produbanco case study The return on assets increased by 95.55%, which is indicative of a notable recovery in profitability. Nevertheless, adjusted liquidity declined by 5.87%, indicating the necessity for further optimization of liquid asset management to mitigate current risks, particularly in the context of a highly volatile economic environment.
- **Internacional**
  In the international context, The return on assets exhibited an improvement of 30.55%, indicative of enhanced operational capacity. Nevertheless, adjusted liquidity declined by 9.93%, emphasizing the necessity to reinforce the management of liquid assets in order to more effectively navigate the inherent uncertainty and risks associated with the global market.

The return on assets exhibited a marked increase of 41.88%, reflecting resilience and a notable enhancement in income-generating capacity. Nevertheless, adjusted liquidity declined by 21.15%, underscoring the imperative for a prompt reassessment of liquid asset management strategies to mitigate prospective risks stemming from the prevailing economic turbulence.

3) EXPLORATION OF VECTORIAL CORRELATIONS

Pre-Pandemic T_1:

- Correlation between the Gross Loan to Assets Ratio (A_4) and the Personal Efficiency Ratio (M_2): The vectors are relatively long and form a small angle with each other, indicating a strong positive correlation.
- Correlation between the Net Non-Performing Assets to Equity ratio (C_3) and Adjusted Liquidity (L_2): These vectors are also significant in length, yet their opposite orientation indicates a negative correlation.

Pandemic T_2:

- Correlation between the Net Non-Performing Assets Ratio (C_3) and the Gross Loan to Assets Ratio (A_4):

TABLE 11. Evolution of CAMEL indicator loadings.

		Weights by Period %		
	VARIABLES	T_1	T_2	T_3
C_3	Unproductive assets to Equity	0.2719	0.1061	0.2347
A_4	Gross loan to Assets	0.0802	0.3514	0.1976
M_2	Personal efficiency	-0.2720	-0.3996	-0.2455
E_1	ROA	0.0188	0.1369	0.1169
L_2	Adjusted Liquidity	0.3570	0.0060	0.2053
	Sume	1.0000	1.0000	1.0000

These vectors demonstrated high variability and high correlation.

Russia-Ukraine War T_3:

- Correlation between Personal Efficiency Ratio ($M2$) y Gross loan to assets Ratio (A_4): The length of these vectors remains substantial, and their positive correlation persists.

G. THIRD STEP: BANK EVALUATION

1) EVOLUTION OF INDICATOR LOADINGS

Table 11 presents the factor loadings calculated by 'Load normalisation' (S) using the equation (28). The table offers a clear representation of the evolution and concentration of the loadings over each period.

a: PRE PANDEMIC T_1

The weighting of the financial indicators highlights the significant influence of adjusted liquidity (L_2), which represents 35.70%, followed by the ratio of Non-performing assets to equity (C_3) with 27.19%. These weightings indicate an interest in maintaining financial stability through adequate liquidity and effective asset management.

b: PANDEMIC T_2

During this period, the ratio of gross loans to assets (A4) was identified as the most critical indicator, with a weighting of 35.14%. This change underscores the heightened significance of asset allocation in the context of the global health crisis. Staff efficiency (M_2), with an absolute weighting of 39.96%, reflects the operational constraints imposed by the pandemic. These constraints resulted in notable cost reductions but also illuminated the challenges associated with maintaining an efficient allocation of staff.

c: RUSSIA-UKRAINE WAR T_3

The influence is represented by a value of 20.53%. However, a more balanced distribution among the indicators was observed. Of particular note is the ratio of non-performing assets to shareholders' equity ($C3$), which increased to 23.47%. This indicates a renewed emphasis on addressing inefficiencies in asset utilization. Additionally, the increase in the ROA ratio (E_1) suggests a shift toward a more adaptive approach to profitability in the context of evolving global challenges.

TABLE 12. Fibonnaci retracement in an uptrend.

Upward Fibonacci trend	Downward Fibonacci trend	Upward Fibonacci	Downward Fibonacci
[76.40 %, >)	[0.00%, 23.61%)	1	5
[78.40%, 61.80%)	[23.61%, 38.21%)	2	4
[38.21%, 78.40%)	[38.21%, 78.40%)	3	3
[23.61%, 38.21%)	[78.40%, 61.80%)	4	2
[0.00%, 23.61%)	(>= , 78.40%]	5	1

2) FIBONNACI RETRACEMENT

Our methodology differs from traditional CAMEL models, which are primarily based on standard deviations relative to the group mean. Instead, we adopt an approach based on Fibonacci retracements, inspired by Luca Pacioli's treatises on the Fibonacci sequence and the golden ratio. This innovative framework optimizes risk thresholds and performance benchmarks for financial indicators J_k in the banking sector.

In the initial stage of this analysis, the time series corresponding to the financial indicators of banks within Segment B were unified using Equation (32). This step ensured consistency and allowed for the construction of a consolidated dataset, $\mathbf{Z}_B$, for subsequent analysis. Specifically, for the L_2 indicator finance, the dataset is organized as a matrix where each row represents the time series of a bank, and the columns correspond to observations over time. The consolidated dataset $\mathbf{Z}_B$ is formally defined as:

$$Z_B = \begin{bmatrix} Banks & March_{\mathbf{2018}} & June_{\mathbf{2018}} & \dots & December_{\mathbf{2023}} \\ \\ \text{Pichincha} & 23.9103 & 16.1355 & \dots & 23.8306 \\ \text{Pacífico} & 29.0032 & 21.9188 & \dots & 27.8665 \\ \dots & \dots & \dots & \dots & \dots \\ \text{Bolivariano} & 38.90 & 33.6173 & \dots & 34.0537 \end{bmatrix}$$

The $\mathbf{Z}_B$ matrix represents the consolidated time series of all banks in segment B for a specific financial indicator J_k, over the period $T_I i$. This representation provides a basis for comparative analysis across the T_i periods: pre-pandemic (T1), pandemic (T2), and Russia-Ukraine war (T3). It serves as an input for applying Fibonacci retracement levels to assess support levels and the performance of the J_K indicator.

3) FIBONACCI CATEGORIZED MATRIX

Using the $\mathbf{Z}_B$ matrix, Fibonacci retracement levels are determined by applying an upward trend to the liquidity indicator (L_2), according to Equation (19). This analysis reflects an improvement in the bank's solvency and predicts a positive impact on both profitability and operating efficiency.

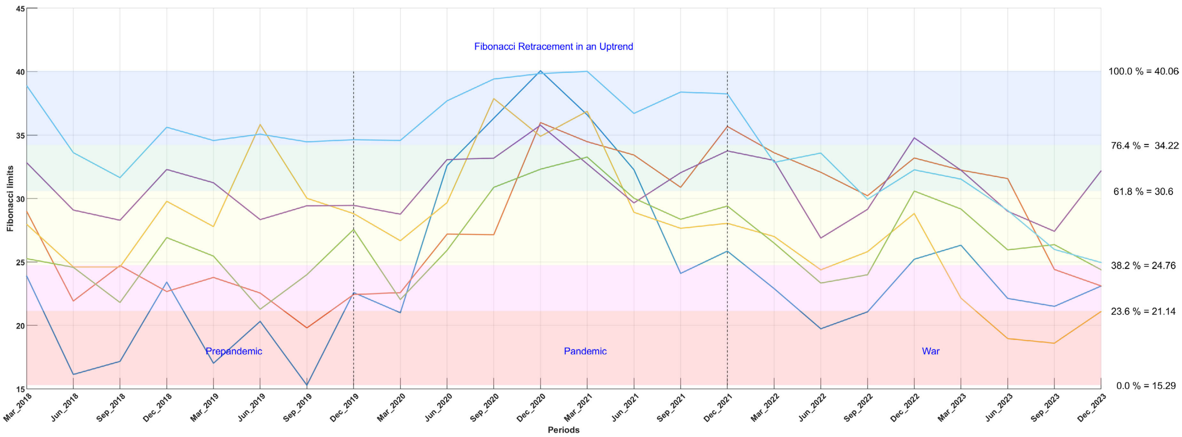


FIGURE 19. Uptrend in ROA L_2.

TABLE 13. Evolución del indicador L_2 en el período T_i.

	Período Pre pandemia							
	Mar 18	Jun 18	Sep 18	Dec 18	Mar 19	Jun 19	Sep 19	Dec 19
Pichincha	2	1	1	2	1	1	1	2
Pacifico	3	2	2	2	2	2	1	2
Guayaquil	3	2	2	3	3	5	3	3
Produbanco	4	3	3	4	4	3	3	3
Internacional	3	2	2	3	3	2	2	3
Bolivariano	5	4	4	5	5	5	5	5

	Período Pandemia							
	Mar 20	Jun 20	Sep 20	Dec 20	Mar 21	Jun 21	Sep 21	Dec 21
Pichincha	1	4	5	5	5	4	2	3
Pacifico	2	3	3	5	5	4	4	5
Guayaquil	3	3	5	5	5	3	3	3
Produbanco	3	4	4	5	4	3	4	4
Internacional	2	3	4	4	4	3	3	3
Bolivariano	5	5	5	5	5	5	5	5

	Período Pandemi Rusia-Ucrania							
	Mar 22	Jun 22	Sep 22	Dec 22	Mar 23	Jun 23	Sep 23	Dec 23
Pichincha	2	1	1	3	3	2	2	2
Pacifico	4	4	3	4	4	4	2	2
Guayaquil	3	2	3	3	2	1	1	1
Produbanco	4	3	3	5	4	3	3	4
Internacional	3	2	2	3	3	3	3	2
Bolivariano	4	4	3	4	4	3	3	3

The values obtained are:

Fibonacci Uptrend L_2

$$
= \begin{cases} Nivel_5: & [34.22, \quad 40.06] \quad \text{(Excellent performance)} \\ Nivel_4: & [30.60, \quad 34.22] \quad \text{(Good performance)} \\ Nivel_3: & [24.76, \quad 30.60] \quad \text{(Stable)} \\ Nivel_2: & [21.14, \quad 24.76] \quad \text{(Risky performance)} \\ Nivel_1: & [15.24, \quad 21.14] \quad \text{(Critical performance)} \end{cases} \tag{36}
$$

Figure 19 illustrates the application of Fibonacci retracement levels with an upward trend to categorize the indicator of Tight Liquidity (L_2) during the pre-pandemic (T_1), pandemic (T_2), and Russia-Ukraine conflict (T_3) periods.

- **Level 5** [78.60 %, 100.00 %):
  The range in question, spanning from 34.22 to 40.06, indicates an indicator status of excellent performance in terms of adjusted liquidity. The achievement of this level of performance by banks is the result of effective liquidity management, which has enabled them to demonstrate a robust capacity to meet their financial obligations and maintain sufficient reserves.
- **Level 4:** [61.80 %, 78.60 %):
  In the range between 30.60 and 34.22, this level indicates a state of good liquidity performance. Banks in this category have adequate reserves and demonstrate prudent liquidity management, ensuring stability and coverage of financial needs.
- **Level 3** [38.20 %, 61.80%):
  This range, between 24.76 and 30.60, reflects a stable state of the indicator, implying that liquidity levels are sufficient, but without a significant increase in the capacity to respond to additional financial demands.
- **Level 2** [23.60 %, 38.20%):
  With a range of between 21.14 and 24.76, this level indicates a risky performance in terms of liquidity, suggesting that banks could face difficulties in meeting their obligations if liquidity management is not optimised.
- **Level 1** [0.00 %, 23.60%):
  In the range of 15.24 to 21.14, banks are in a critical state of adjusted liquidity. This level represents a vulnerable financial position where the ability to meet obligations could be compromised if corrective action is not taken.

4) FIBONACCI CATEGORIZED MATRIX FOR ADJUSTED LIQUIDITY INDICATOR (L_2)

Table (13) illustrates the evolution of the adjusted liquidity indicator (L_2) in three distinct periods: the pre-pandemic period (T_1), the pandemic period (T_2), and the Russia-Ukraine war period (T_3). Each cell of the table represents the performance of a specific bank Pichincha, Pacífico, Guayaquil, Produbanco, Internacional, and Bolivariano during a particular time interval. The values range from 1 to 5, with lower values indicating weaker liquidity conditions and higher values representing greater liquidity resilience.

These ratios facilitated the identification of potential support and resistance levels that might emerge following a significant indicator move. With this approach, we aimed to

TABLE 14. Solvency rating in the period k_i.

	Fibonacci Levels					Weighted Performance					
$k_8 = December_{2019}$ Pre-pandemic											
Weighted W						0.2719	0.0802	0.2720	0.0188	0.3570	
Bancos	C_4	A_4	M_2	E_1	L_2	C_4	A_4	M_2	E_1	L_2	Bank ranking
Pichincha	5	3	1	3	2	1.3596	0.2406	0.2720	0.0565	0.7141	52.86
Pacifico	4	5	2	5	2	1.0877	0.4011	0.5440	0.0942	0.7141	56.82
Guayaquil	3	4	3	5	3	0.8158	0.3209	0.8159	0.0942	1.0711	62.36
Produbanco	3	4	3	3	3	0.8158	0.3209	0.8159	0.0565	1.0711	61.60
Internacional	4	4	5	4	3	1.0877	0.3209	1.3599	0.0753	1.0711	78.30
Bolivariano	4	3	4	3	5	1.0877	0.2406	1.0879	0.0565	1.7852	85.16
$k_{16} = December_{2021}$ Pandemic											
Weighted W						0.1061	0.3514	0.3996	0.1369	0.0060	
Bancos	C_4	A_4	M_2	E_1	L_2	C_4	A_4	M_2	E_1	L_2	Bank ranking
Pichincha	5	2	2	2	3	0.5305	0.7028	0.7993	0.2737	0.0180	46.49
Pacifico	1	3	3	1	5	0.1061	1.0541	1.1989	1.1369	0.0301	50.52
Guayaquil	2	4	4	3	3	0.2122	1.4055	1.5986	0.4106	0.0180	72.88
Produbanco	1	4	3	2	4	0.1061	1.4055	1.1989	0.2737	0.0240	60.17
Internacional	3	3	5	3	3	0.3183	1.0541	1.9982	0.4106	0.0180	75.99
Bolivariano	4	3	5	3	5	0.4244	1.0541	1.9982	0.4106	0.0301	78.34
$k_{24} = December_{2023}$ War Rusia-Ucranine											
Weighted W						0.2347	0.1976	0.2455	0.1169	0.2053	
Bancos	C_4	A_4	M_2	E_1	L_2	C_4	A_4	M_2	E_1	L_2	Bank ranking
Pichincha	5	3	3	3	2	1.1734	0.5927	0.7366	0.3508	0.4106	65.28
Pacifico	5	4	5	5	2	1.1734	0.7902	1.2277	0.5846	0.4106	83.73
Guayaquil	4	5	4	5	1	0.9387	0.9878	0.9821	0.5846	0.2053	73.98
Produbanco	4	5	4	3	4	0.9387	0.9878	0.9821	0.3508	0.8212	81.61
Internacional	5	5	5	4	2	1.1734	0.9878	1.2277	0.4647	0.4106	85.34
Bolivariano	5	5	5	4	3	1.1734	0.9878	1.2277	0.4677	0.6159	89.45

improve the detection of anomalies in financial indicators that exceeded established risk thresholds.

5) BANK PERFORMANCE

The matrix $\boldsymbol{W}$, was obtained using equation (35),which calculates the weighted product of the adjustment factors α_j and the categorised F_{ij} of the financial indicators for each bank, based Fibonacci retracements. This matrix establishes the relevance of each variable within the observed quarter k and provides an overall assessment of how each bank ranks relative to its group. It also identifies the specific weight of each financial indicator in the analysis of bank performance for the quarter under review.

The key benefit of this approach is its capacity to visually represent the ranking component in comparison to other methodologies. Furthermore, it enables the illustration of this component at the level of each indicator, along with the incorporation of the relevance of the factor loadings associated with each indicator individually.

La Tabla (14) presents a consolidated view of the categorised Fibonacci levels for each financial indicator, assessed at the level of each bank in the different k quarters. The methodology employs a weighting system that utilises the ratios of each financial indicator (C_4, A_4, M_2, E_1 y L_2) to determine the relative importance of the Fibonacci levels. This process allows us to calculate a weighted return for each indicator, which is then aggregated at the bank level and rescaled to determine the bank performance of each institution in each period k_i.

The months of December have been taken as the reference for the closures of the following periods: Pre-Pandemic (T_1), Pandemic (T_2), and Russia-Ukraine War (T_3). The key findings were as follows:

a: BANK PICHINCHA

- **Pre-pandemic:** Bank ranking of 52.86, showing low Fibonacci levels in staff efficiency (E_1) and adjusted liquidity (L_2), suggesting moderate growth in terms of solvency.
- **Pandemic:** Bank ranking decreased to 46.49, with low levels in gross loans to assets (A_4), staff efficiency (E_1), and adjusted liquidity (L_2), reflecting the impact of the pandemic.
- **Russia-Ucranine war:** Bank ranking of 65.28, with improvements in several Fiboananci levels of the indicators, although adjusted liquidity (L_2) remains low, indicating a move towards stability that is still developing.

b: BANK PACIFIC

- **Pre-pandemic:** Bank ranking of 56.82, with low levels of personnel expenses (M_2) and adjusted liquidity (C_3), reflecting moderate stability with implicit risks in the efficiency of resource management.
- **Pandemic:** Bank ranking decreased to 50.52, placing it at critical Fibonacci levels in gross loans to assets (A_4) and ROA (E_1), evidencing the pressure exerted on its financial structure in this challenging period.
- **Russia-Ucranine war:** Notable recovery in Bank ranking of 83.73, showing improvement at most Fibonacci levels, although a low level of adjusted liquidity (L_2)

persists, suggesting solid resilience in a context of increasing uncertainty.

c: BANK GUAYAQUIL

- **Pre-pandemic:** Bank ranking of 62.36, with average Fibonacci levels in gross loans to assets (A_4), staff efficiency (M_2), and adjusted liquidity (L_2), while maintaining a consistent base financial structure.
- **Pandemic:** Bank ranking decreased to 72.88, with low levels of liquidity (L_2) compared to other competing banks, evidencing its ability to sustain liquid assets in an adverse environment.
- **Russia-Ucranine war:** Bank ranking of 73.91, with moderate levels in most indicators, although with a low level of non-performing assets (C_4), indicating a favourable adaptation and reinforcing its stability in an uncertain environment.

d: BANK PRODUBANCO

- **Pre-pandemic:** Bank ranking of 61.60, with moderate levels in all financial indicators, reflecting a stable financial structure within the sector.
- **Pandemic:** Bank ranking reduced to 60.17, with a low level of non-performing assets (C_3), affected by the impact of the pandemic.
- **Russia-Ucranine war:** Bank ranking of 81.61, with moderate levels in all indicators, indicating a favourable adjustment and reinforcing its stability in an environment of uncertainty.

e: BANK INTERNACIONAL

- **Pre-pandemic:** Bank ranking of 78.30, with high levels of non-performing assets (C_4), gross loans to assets (A_4) and ROA (E_1), and good staff efficiency (M_2), giving a sound financial structure in this period.
- **Pandemic:** Bank ranking ratio fell slightly to 75.99, reflecting a slight decline in the above indicators and demonstrating the Bank's ability to withstand the impact of the pandemic without major changes to its financial stability.
- **Russia-Ucranine war:** Bank ranking increased to 85.34, with excellent levels of non-performing assets (C_4), gross loans to assets (A_4) and staff costs (M_2), and a moderate level of ROA (E_1).

f: BANK BOLIVARIANO

- **Pre-pandemic:** Bank ranking of 85.16, highlighted by high levels of non-performing assets (L_2) and personal efficiency (E_1), and an excellent level of adjusted liquidity (E_1), reflecting a sound financial structure during this period.
- **Pandemic:** A high Bank ranking ratio of 78.35, with a slight adjustment, shows Banco Bolivariano's ability to maintain financial stability despite the pressures generated during the pandemic.
- **Russia-Ucranine war:** Bank ranking increased to 89.45, reaching high levels in all indicators, demonstrating robust resilience and reinforcing the bank's solidity in an environment of uncertainty.

H. BANKING STRATEGIES

The evolution of the Fibonacci categorization frames the strategy followed by the bank in the financial environment it faced in the different periods T_i. In Figures 112, we can see how the financial indicators J_k followed a strategy defined by each bank, depending on its internal capabilities and the instructions of the financial management.

VI. DISCUSSION AND CONCLUSION

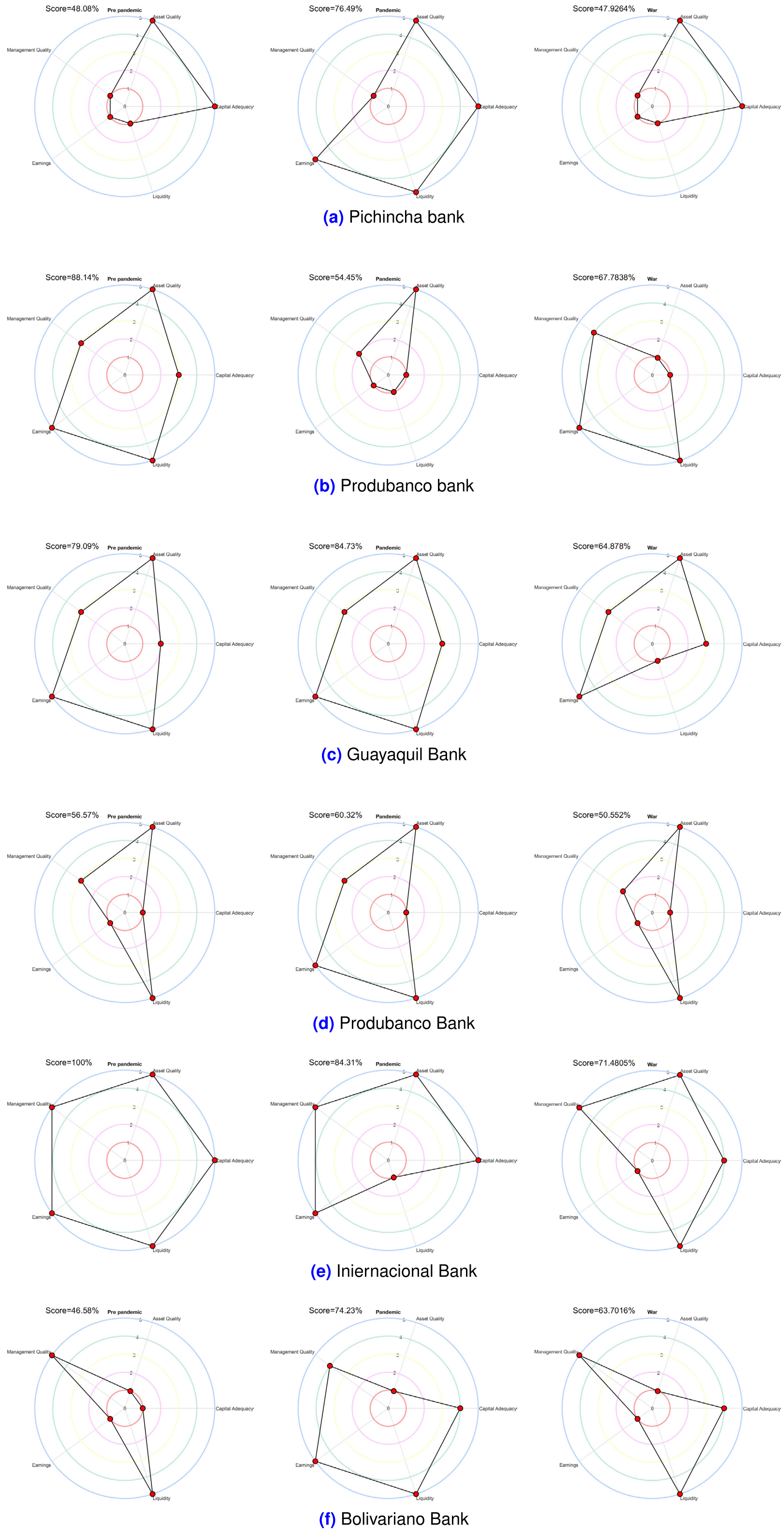
A. DISCUSSION

1) FLUCTUATIONS IN THE R_V MATRIX

The results of this study demonstrated that the correlation matrix $\boldsymbol{R}_v$ underwent compositional alterations as a consequence of the global health crisis precipitated by the Coronavirus (Covid-19) during the period designated as T_2, and the geopolitical conflict between Russia and Ukraine during the period designated as T_3 (See Section V-C).

- **Pre-pandemic Period (T_1):** A high level of correlation was identified, which is indicative of a period of financial stability. This suggests that the market is predictable and stable.
- **Pandemic Period (T_2):** The global health crisis precipitated a sharp decline in correlations, indicating a disruption of historical financial relationships. The elevated volatility observed in recent times serves to illustrate the acute sensitivity of the banking sector to external shocks.
- **Russia-Ukraine War Period (T_3):** During the initial stages of the conflict, correlations remained high, which can be attributed to the government's sustained implementation of mitigation strategies in response to the impact of the Coronavirus. However, as the Russia-Ukraine conflict intensified and the European Economic Community (EEC) introduced sanctions against Russia, correlations remained high, likely due to the government's continued implementation of mitigation strategies in response to the impact of the Coronavirus.

A comparison of our results with those of a study by Misztal (Misztal, 2020) [60], which assessed the Rv matrix in response to external events in Poland from 2000 to 2017, shows that Mistal's focused on the temporal and spatial structure of the data over an 18-year period. In contrast, our study examines multiple Ti periods, revealing detailed trends at the k-quarter level, and not only assessing the position of banks at the end of December each year, providing a deeper understanding of the impact on the $\boldsymbol{R}_v$ matrix. It is important to bear in mind the limitations inherent in contrasting each T_i period, as they represent a crisis period or environment, such as the pandemic and the Russia-Ukraine territorial crisis.



(a) Pichincha bank

(b) Produbanco bank

(c) Guayaquil Bank

(d) Produbanco Bank

(e) Iiernacional Bank

(f) Bolivariano Bank

FIGURE 20. Evolution of risk rating.

It should be noted that comparisons between T_i periods can only be made if the intervals in question meet the required statistical tests, which are discussed in the next section. (See Section V-B)

2) COMPROMISE MATRIX

The results of the Commitment Matrix, $\boldsymbol{C}_{ij}$, revealed notable fluctuations in the J_k financial indicators of the I_k banks for each T_i period, as illustrated in Figure 1. The details of the changes in the Financial Financial Indicators can be found in section (4.3.1. Matriz Compromiso).

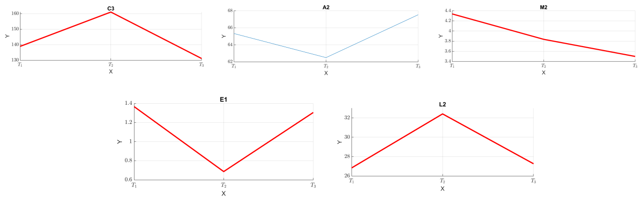


FIGURE 21. Evolution of the compromise matrix.

The observed fluctuations in financial indicators across T_i periods reflect the resilience of banks to adverse economic and geopolitical conditions. During the pandemic, banks increased liquidity (L_2) and adjusted asset management and staff efficiency (M_2), which enabled them to navigate the health crisis. In the period of the Russia-Ukraine war, most indicators stabilised, indicating that banks have begun to adapt to the new post-pandemic normal.

B. CAMELS WEIGHT EVOLUTION

In this study, we analyse how the Ecuadorian banking sector has adjusted the weight of financial indicators J_k over three different periods (T_i), reflecting changes in management strategies in the face of different economic environments.

- **Pre-pandemic Period (T_1):** The data show that the predominant factors were adjusted liquidity L_2 with a weight of 0.3570, non-productive assets over capital C_3 with a weight of 0.2719 and personnel efficiency M_2 with 0.2720. This suggests a focus on accumulating liquidity as a safety measure, efficiently managing non-productive assets and controlling operating costs, seeking stability and competitiveness in a stable environment. This pre-pandemic strategy prioritised financial strength and operational efficiency as the basis for institutional strengthening.
- **Pandemic Period (T_2):** With the arrival of the pandemic (T_2), staff efficiency M_2 became the dominant factor with a weight of 0.3996, followed by gross loans to assets A_4 with 0.3514. This change reflects the need to adapt banking operations to a crisis environment, prioritising the optimisation of human resources and a prudent approach to credit risk management to meet the complex economic challenges posed by the pandemic.
- **Russia-Ukraine War Period (T_3):** During the Russia-Ukraine war period (T_3), a more balanced distribution of the weights assigned to financial indicators is observed, suggesting an adaptive approach to bank management in the face of uncertainty. The data show that non-performing assets to capital C_3 and adjusted liquidity L_2 regain relative importance, with weights of 0.2347 and 0.2053 respectively, while staff efficiency M_2 and gross loans to assets A_4 retain values of 0.2455 and 0.1976. This allocation reflects the banks' attempt to balance their exposure to operational risks, liquidity and asset quality, adapting to a volatile context that requires flexibility and prudence in the management of financial resources. According to the results of the (See Section V-G).

Studies by Dr Patrick Staples et al. explore the performance of robust and accurate prediction of longitudinal data using Hilbert-Schmidt decomposition (HSIC) as a supervised loss function. Hilbert-Schmidt decomposition (HSIC) as a supervised loss function. This approach allows dimensionality reduction both between and within clusters [61] clusters. The essence of this method is that the data are first sorted by i (individuals), j (variables) and k (repeated measures), then individual PCA is applied to each individual, followed by global PCA to the combined longitudinal data. Finally, the individual and Finally, the individual and global scores are compared, consistency is assessed, and regression is performed on the principal components of the scores to make predictions.

- **Net Non-Productive Asests to Equity Ratio C_3:** A rise was observed from 0.1558 in T_1 to 0.1756 in T_2, reaching 0.2015 in T_3. This increase reflects an increasing proportion of non-performing assets relative to total capital, which may indicate an increase in solvency risk for the assessed banking entities.
- **Personal efficiency M_2:** This indicator varied significantly from 0.1408 in Q_1 to 0.2939 in Q_2 and moderated to 0.2145 in Q_3. The increase in Q_2 reflected a strategic shift due to the closure of offices during the pandemic, which led banks to focus on virtual channels and reduce staff operating expenses due to teleworking.

C. HJ-BIPLOT

The HJ Biplot graph revealed notable variations in the scenarios represented across the three distinct T_i periods. These variations serve to illustrate the contributions of the principal components and the position of the banks and financial indicator vectors within each period. The evolution of these principal components demonstrated that external shocks, such as the pandemic and the territorial conflict between Russia and Ukraine, affected the Euclidean representation of the HJ biplot with respect to the Personal Efficiency indicator in banks (M_2) and the Return on Assets (ROA) indicator (E_1).

The increase in the variability explained by the second component during the crises ($T_1 = 37.2\%$; $T_2 = 35.55\%$; $T_3 = 27.31\%$) indicates that previously secondary factors are becoming increasingly important, suggesting the necessity to adapt to new risks and challenges in times of uncertainty. In the pre-pandemic period, banks and their financial indicators exhibited greater dispersion, which may reflect significant heterogeneity in performance and financial strategies prior to the pandemic.

- **Pre-pandemic Period (T_1):** In the period preceding the pandemic (T_1), banks and their financial indicators exhibited greater dispersion, which may reflect substantial heterogeneity in performance and financial strategies prior to the pandemic.

TABLE 15. Descriptive stadistics of indices.

Inidcadors	Period	Mean	Std Desv.	Median	Min	Max	Skew	Kurtosis
Pre-pandemic	C_1	8.8708	1.1695	8.8729	6.7541	11.4248	0.1829	2.3880
	C_2	5.3868	3.3051	5.8213	0.5996	10.5959	-0.0323	1.8027
	A_1	84.9138	3.9617	86.2103	77.0080	91.1926	-0.8656	2.8679
	A_2	2.1843	1.0197	1.8325	1.0919	4.1777	0.5124	1.7632
	M_1	4.3810	0.8663	4.5640	2.9556	5.8893	0.1116	2.1621
	M_2	1.3648	0.2478	1.2992	1.0402	1.7839	0.5350	1.7547
	E_1	1.4118	0.2623	1.3282	1.0321	1.8908	0.5438	1.8410
	E_2	13.8390	1.9331	14.2486	9.3951	17.0986	-0.6294	2.8052
	L_1	25.1117	5.8303	25.5054	16.2083	32.2265	-0.2392	1.5806
	L_2	26.7392	5.9198	27.6729	15.2927	35.8331	-0.1086	2.0556
Pandemic	C_1	8.4459	0.9992	8.3635	6.8401	10.4512	0.2947	2.3213
	C_2	5.6721	3.4088	5.5625	0.9193	12.3865	0.3600	2.2214
	A_1	80.7503	8.5523	83.2460	56.7517	91.5507	-1.5740	4.7434
	A_2	2.2303	1.3401	1.7408	0.9846	6.4918	1.6642	5.6648
	M_1	3.9476	0.7231	3.9648	2.7056	5.3090	0.1616	2.2145
	M_2	1.2151	0.1837	1.1966	0.9241	1.5661	0.4015	2.2850
	E_1	0.6274	0.2460	0.5885	0.1315	1.0193	-0.1408	2.0117
	E_2	6.3332	2.5858	6.5876	1.3063	11.1034	-0.0556	1.9298
	L_1	28.8071	5.3259	28.7441	18.1288	39.6616	-0.0071	2.6974
	L_2	31.8956	5.7232	32.8340	20.9969	40.0639	-0.3613	2.0846
Pandemic	C_1	7.9678	0.7437	7.9554	6.4021	8.9462	-0.4491	2.3293
	C_2	5.2050	3.9116	4.7206	0.7210	14.0837	0.5847	2.2510
	A_1	79.8029	8.9173	83.4271	58.0499	87.6749	-1.5621	3.8519
	A_2	1.7412	0.8770	1.2960	0.7067	3.6471	0.6970	2.0981
	M_1	3.7585	0.6945	3.7547	2.5527	5.0107	0.1436	2.3163
	M_2	1.1568	0.1929	1.1244	0.8752	1.6784	0.7461	3.3435
	E_1	0.7521	0.2702	0.7715	0.0812	1.1687	-1.0245	3.9151
	E_2	8.1005	3.0597	8.8092	0.6989	12.3490	-1.0434	3.6112
	L_1	29.3434	5.3545	28.7792	19.0914	38.0372	-0.0635	2.0541
	L_2	32.3901	4.2188	32.4994	24.0975	40.0188	-0.0323	2.1565
War	C_1	8.2422	1.1498	8.3615	5.9411	10.6910	0.0661	2.6921
	C_2	4.7314	3.4669	4.1225	0.7299	11.6511	0.4658	1.9110
	A_1	83.6812	7.8195	86.4220	63.9020	90.0664	-1.6350	4.0771
	A_2	1.5854	0.8950	1.2760	0.5567	3.2726	0.5987	1.9518
	M_1	3.6509	0.7048	3.4890	2.5849	4.9053	0.3637	2.0793
	M_2	1.0806	0.1894	1.0276	0.8878	1.4912	1.1821	3.2292
	E_1	1.2185	0.2262	1.1618	0.7648	1.5935	0.1202	2.0465
	E_2	12.7953	2.4141	12.2956	7.9600	17.3613	0.2542	2.3287
	L_1	26.2340	6.1952	27.1309	14.6898	39.2034	0.0603	2.3897
	L_2	28.3698	4.3908	28.9813	19.7328	34.7808	-0.2890	1.9258
	E_2	12.7953	2.4141	12.2956	7.9600	17.3613	0.2542	2.3287
	L_1	26.2340	6.1952	27.1309	14.6898	39.2034	0.0603	2.3897
	L_2	28.3698	4.3908	28.9813	19.7328	34.7808	-0.2890	1.9258

- **Pandemic Period (T_2):** During the pandemic period (T_2), the reorientation of some vectors indicated a change in the relevance of certain financial indicators, such as gross loans to assets (A_4) and staff efficiency (M_2).
- **Russia-Ukraine War Period (T_3):** In the period of the Russia-Ukraine war (T_3), some banks exhibited improvements in the indicators of Non-Performing Assets to Capital (C_3), Staff Efficiency (M_2) and Return on Assets (ROA) (E_1). These changes are reflected in the direction and magnitude of the corresponding vectors for return on assets (ROA) (E_1) and gross loans to assets (A_4). (See Section V-G).

1) CORRELATION IN THE HJ-BIPLOT

a: PRE-PANDEMIC T_1.

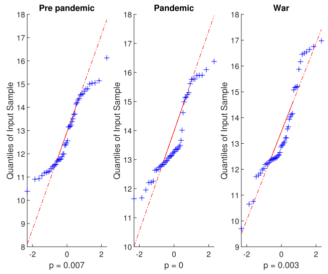
- A strong positive correlation has been found between the gross loan to assets indicator (A_4) and return on assets ROA (E_1). This relationship suggests that loan portfolio expansion is associated with increased profitability, reflecting effective management and solid growth in a stable economic environment.
- There is also a correlation between non-performing assets (C_3) and adjusted liquidity (L_2), suggesting that the level of non-performing assets has an impact on liquidity, reflecting a prudent financial risk mitigation strategy.
- Finally, there is an inverse relationship between unproductive assets (C_3) and personnel costs (M_2), which may indicate a strategy of controlling operating costs in the presence of unproductive assets. (textcolorblue4.2.3.2. HJ biplot analysis per pre-pandemic period T_1).

b: PRE-PANDEMIC T_1.

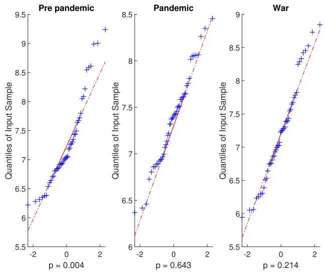
- A strong positive correlation has been found between the gross loan to assets indicator (A_4) and return on assets ROA (E_1). This relationship suggests that loan portfolio expansion is associated with increased profitability, reflecting effective management and solid growth in a stable economic environment.
- There is also a correlation between non-performing assets (C_3) and adjusted liquidity (L_2), suggesting that the level of non-performing assets has an impact on liquidity, reflecting a prudent financial risk mitigation strategy.
- Finally, there is an inverse relationship between unproductive assets (C_3) and personnel costs (M_2), which may indicate a strategy of controlling operating costs in the presence of unproductive assets. (textcolorblue4.2.3.2. HJ biplot analysis per pre-pandemic period T_1).

c: PRE-PANDEMIC T_2.

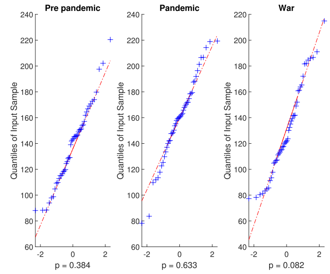
- The relationship between adjusted liquidity L_2 and return on assets ROA $E1$ shows a strong positive correlation. This suggests that an increase in adjusted



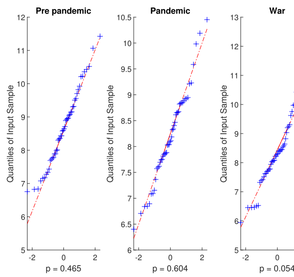
(a) C_1 Solvency



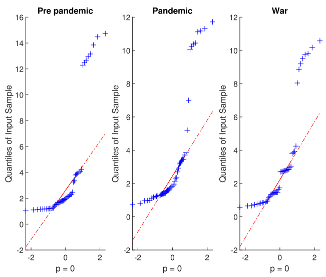
(b) C_2 Capital Adequacy



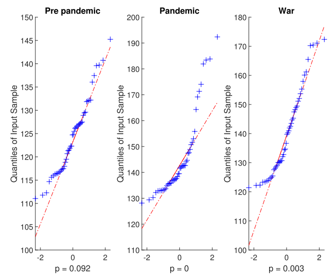
(c) C_3 Unproductive assets to Equity



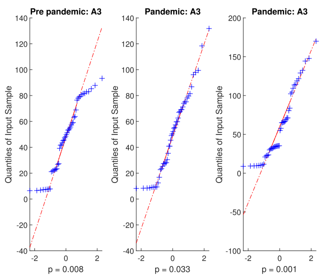
(d) C_4 Net Capitalization



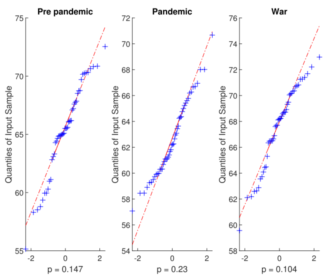
(e) A_1 Loan delinquecy



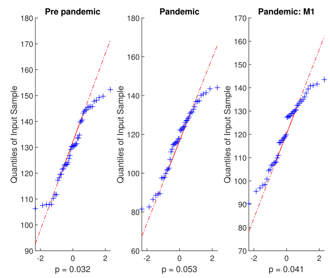
(f) A_2 Level of absorption



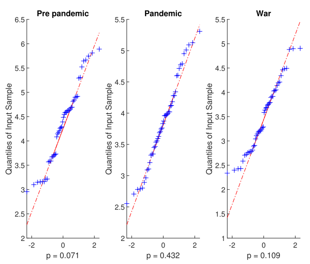
(g) A_3 Gross portafolio coverage



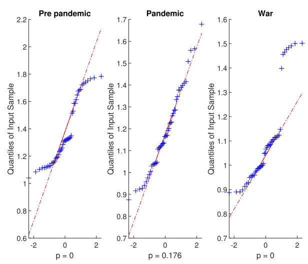
(h) A_4 Gross loan to Assets



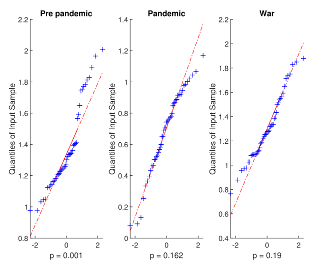
(i) M_1 Management administrative



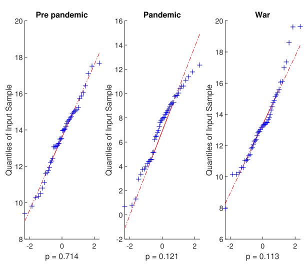
(j) M_2 Operating efficiency



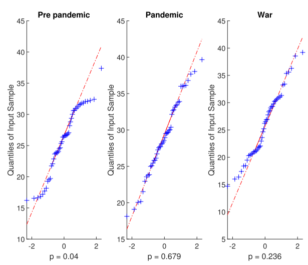
(k) M_3 Personal efficiency



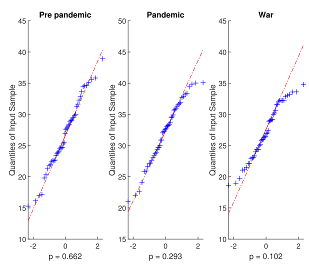
(l) E_1 Return on Assets ROA



(m) E_2 Return on Assets ROE

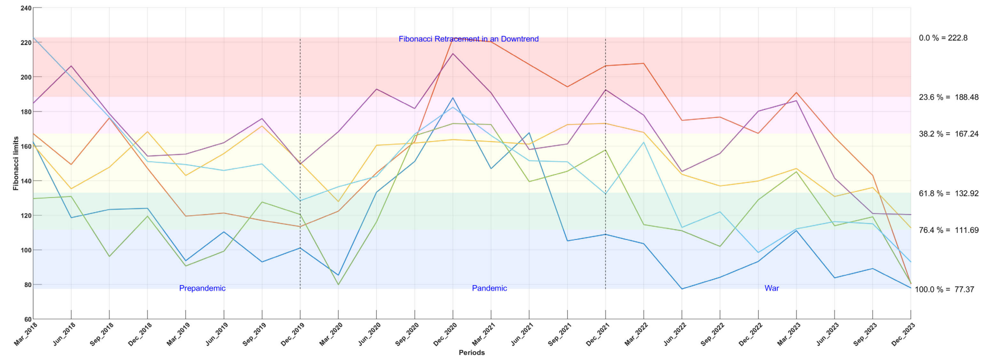


(n) L_1 Immediate Liquidity

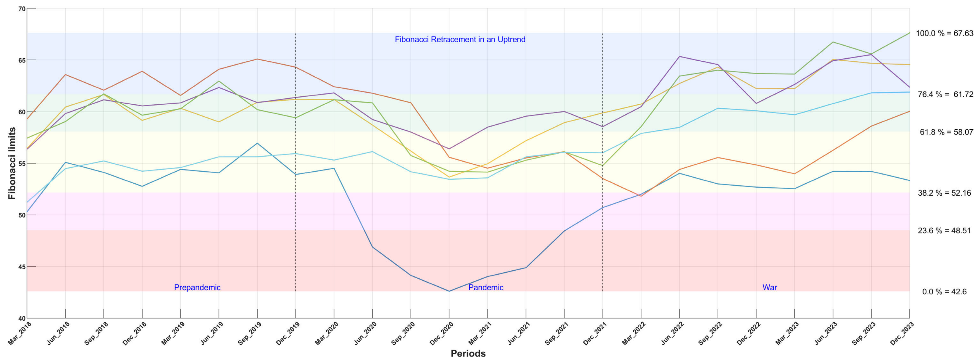


(o) L_2 Tight Liquidity Adjusted

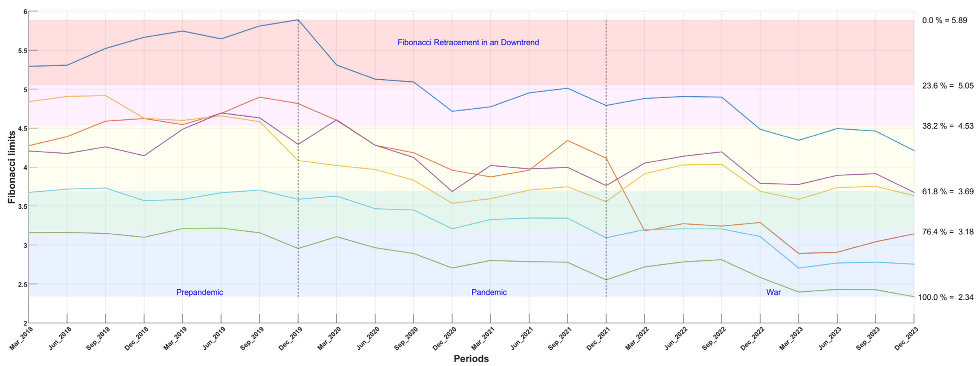
FIGURE 22. **Shafiro normality test.**



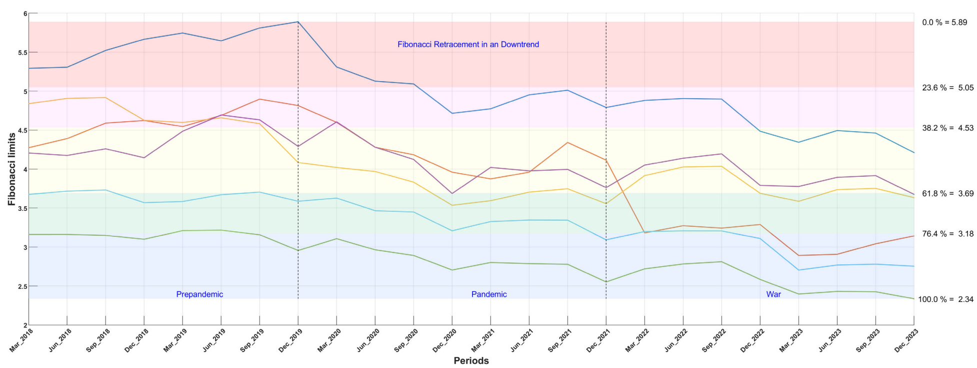
(a) C_3 Unproductive Assets to Equity



(b) A_4 Gross Loan to Assets



(c) M_2 Personal Efficiency



(d) E_1 Return on Assets - ROA

FIGURE 23. Fibonacci quarterly *k* retracement analysis.

liquidity is associated with an improvement in ROA, suggesting that greater liquidity availability supported the overall performance of bank assets during the pandemic.
- Similarly, during the pandemic, there was a positive correlation between non-performing assets to capital C_3 and gross non-performing loans to assets A_4, reflecting a relationship in which non-performing assets affected banks' ability to maintain stable capital.
- The observed changes in the magnitude and direction of the staff efficiency indicator M_2 suggest a possible reassessment of operational priorities and adjustments in risk management, reflecting how banks have adapted their approach to virtual operations and teleworking in response to mobility constraints. (textcolorblue4.2.3.2. HJ biplot analysis per pre-pandemic period T_1).

d: PRE-PANDEMIC T_3.

- The positive correlation between gross loans to equity A_2 and adjusted liquidity L_2 suggests that, despite external challenges, banks have been able to maintain adequate liquidity while expanding their loan portfolios.
- The inverse correlation between staff efficiency M_2 and gross loans to equity A_4 suggests that a greater focus on operational efficiency was associated with a reduction in loan growth, possibly as part of a risk management strategy. (textcolorblue4.2.3.2. HJ biplot analysis per pre-pandemic period T_1).

D. FIBONACCI CATEGORIZED MATRIX

Abuzarqa and Tarnóczi evaluated the factors comprising the CAMELS methodology for commercial banks in Qatar and Kuwait to assess the differences between financial indicator ratios and found that the best performance was that of Qatari banks by comparing standard deviations citeb65. In our study, we develop a method based on Fibonacci retracements to identify risk thresholds in the banking sector. This approach allows us to more accurately detect anomalies in financial indicators, overcoming the limitations of traditional CAMEL methods based on standard deviations.

Unlike traditional methods, our approach uses Fibonacci retracements to set thresholds that are more dynamic and sensitive to the specific conditions in the banking sector. This makes it possible to identify both improvements and deteriorations in financial indicators without relying on the mean, allowing us to assess whether a banking institution has actually improved its relative position vis-à-vis its peers, even in contexts where all institutions face similar shocks.

VII. CONCLUSION

The results of this study align with the stated objectives presented in the introduction. The following section presents the specific findings of the study. The aforementioned findings are in alignment with the study's stated objectives:

1) The correlation matrix, $\boldsymbol{R}_V$, indicates that the Ecuadorian banking sector, which is susceptible to external shocks, has been significantly affected by the COVID-19 pandemic (T_2) and the Russia-Ukraine territorial crisis (T_3). The correlation coefficients between the vectors k, representing k quarters, show how these shocks have altered the correlations, thus evidencing the direct impact of external events on the stability of the Ecuadorian banking sector. This is in line with the Objetive 1.
2) The CPTA model enabled the identification of the weights or factor loadings that elucidate the significance of the J_k financial indicators that constitute the CAMELS methodology. The model demonstrated how the coefficients are affected by periods of crisis, namely the 2019 novel coronavirus pandemic and the Russia-Ukraine territorial crisis. This enabled the observation of variations in the ratios during the T_i periods, the assessment of the relevance of the indicators and the analysis of the financial strategies employed to cope with these crisis moments. The CTPA model provides valuable guidance to financial managers in times of turbulence in the banking sector, which is in line with the Objetive 2.
3) The utilization of the HJ-Biplot enables the comparison of vector correlations between disparate financial indicators, thereby facilitating the identification of strategic patterns within the banking sector. This technique enables the evaluation of the homogeneity or diversity of the strategies pursued by banks within the analysed segment, with a particular focus on the proximity or divergence between them. The magnitude and direction of the vectors are of significant value in understanding the prioritization of strategies. Such knowledge is of paramount importance in understanding the adaptability of the banking sector and its ability to respond effectively in periods of crisis or uncertainty. This is consistent with the Objetive 3.
4) The integration of Fibonacci Retracements into the CPTA provides a more dynamic and accurate assessment of the performance of financial indicators, overcoming the limitations of traditional CAMEL methods. This allows for the detection of both upward and downward trends, establishing the relative position and resilience of each indicator against its segment due to the impacts of crisis periods T_i. This improvement better detect anomalies in financial indicators, even when all banks are similarly affected Objetive 4.

APPENDICES

See Table 15 and Figures 22, 23.

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