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Efficient Insolvency Detection in Iranian Banks through Statistical Process Control: A Real Case Study

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Abstract

Bank insolvency poses significant risks to economic stability, particularly in fluctuating financial ecosystems. This study introduces a novel framework that integrates Statistical Process Control with capital adequacy assessments to improve early detection and resolution of bank insolvency. Unlike traditional models that rely on static thresholds or historical analysis, SPC enables dynamic, real-time monitoring of capital adequacy trends. Our model identifies critical insolvency indicators through SPC methodologies by analyzing ten major Iranian banks over a decade, and categorizes them as well-capitalized, medium-capitalized, and small-capitalized banks. Results reveal that all participating banks show statistically out-of-control processes, suggesting heightened insolvency risks. Specifically, six banks were consistently below the lower specification limit, pointing to the efficacy of SPC in preemptively addressing insolvency challenges. This model advocates ongoing monitoring and strategic financial adjustments to stabilize the overall economic environment.

Keywords
Statistical Process Control; Bank Insolvency; Capital Adequacy; Financial Stability

1. Introduction
Bank insolvency has been a significant issue in the global economy for the past three decades, and it has increased in recent years due to financial crises (Fox 2022). Insolvency occurs when a bank is unable to meet its financial obligations and fails to pay its debt. The negative effects of insolvency go beyond the bank itself, impacting depositors, businesses, and the broader economy. Insolvency can cause slower economic growth, increased losses in insolvent banks, and negative government policy changes (Fox 2022), liquidation losses (Siebenbrunner et al. 2024), etc. Insolvency stems from multiple interconnected factors, which this paper groups into three key drivers: recognized loss, Non-Performing Loans (NPLs), and interest rate shocks. Improper accounting practices, such as miscalculating profits or recognizing revenue without actual cash flow, artificially inflate financial health, masking true insolvency risks (Shirijian et al. 2023). A deficiency in the allowance for doubtful accounts erodes capital, accelerating banks' path to insolvency. Meanwhile, a credit crunch, where banks lose the capacity to lend, creates a vicious cycle: surging demand for scarce loans strains the system further, pushing weaker institutions toward collapse. At its core, insolvency often reveals a system failing to reconcile its books with economic reality. Figure 1 shows the multiple reasons for insolvency to occur.

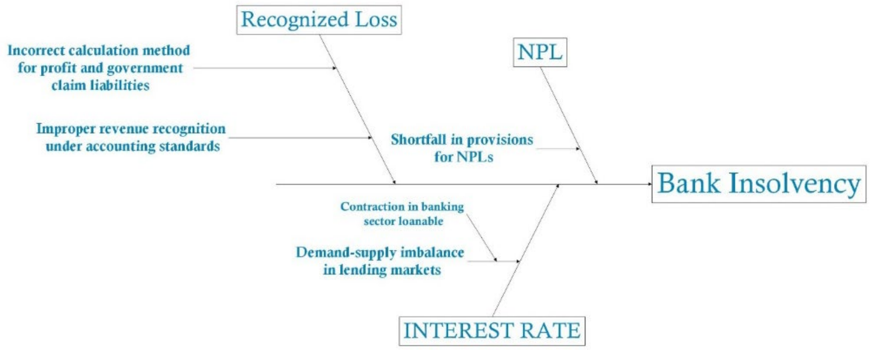

Figure 1. Cause and effect diagram (Shirijian et al., 2022)

As a result of this problem, various models have been introduced for the early prevention and detection of insolvency. This article uses a statistical process control model (SPC) to examine ten Iranian banks' insolvency. SPC is a powerful tool used to detect variations that lead to failure. SPC analyzes the process at a continuous level, which leads to detecting issues early, reducing waste, and increasing productivity (Montgomery and Runger 2010). Unlike other traditional process control methods, SPC doesn't rely on inspecting finished products, instead, it uses real-time monitoring to prevent failure before it occurs. SPC is widely used in fields such as manufacturing, healthcare, and logistics to maintain process stability and productivity.

Other methods are also introduced to address insolvency problems. The CAMELS model is used as a method to detect insolvency, investigating capital adequacy, asset quality, management quality, earnings, liquidity, and sensitivity to market risk (Fox 2022). This method reflects a bank's overall performance and stability and helps bank managers to enhance their financial environment.Dynamic models are a common method to detect insolvency. A dynamic model is a predictive or econometric model that analyzes how a bank’s financial indicators, such as financial shock, capital, rate of return (ROR), etc., evolve to assess the likelihood of insolvency (Shome et al. 2025).Machine learning is a set of data-driven algorithms that can learn patterns based on historical data. It can be trained to detect and predict insolvency by using historical data of banks and credit unions (De Jesus and da Nóbrega Besarria, 2023).Z-score is a financial metric used to determine the risk of insolvency or bankruptcy in firms, including banks. It combines key financial ratios, such as capital and ROR, into a single value that indicates the risk of insolvency (Mercadier and Strobel 2024).

One of the key factors influencing bank insolvency is capital adequacy. Capital is used as a financial buffer, which allows banks to take in economic shocks, loan defaults, and operational risks (Kaufman 2006). A well-capitalized bank can endure financial crises. On the other hand, an undercapitalized bank is vulnerable. Regulatory frameworks indicate minimum capital requirements to reduce insolvency risk. Capital adequacy has to be monitored and adjusted based on economic conditions, market volatility, and a bank's risk exposure. For this purpose, SPC is used. By applying SPC methods, bankers are able to track fluctuations in capital levels, detect signs of insolvency, and take corrective actions before it’s too late.

In this study, the SPC model is used to analyze the capital adequacy of ten Iranian banks over the past ten years. The amount of reserved capital of each bank is compared against the regulatory standards set by the government. This approach provides insights into methods of enhancing resilience against insolvency and can help bankers in determining patterns of instability (Azam et al. 2023). By using this model, bankers can adapt a strategy for risk management (Unda and Ranasinghe 2021), regulatory compliance (Conlon et al. 2020) and long-term financial stability(Marcelin et al. 2022).The paper is structured as follows. Section 2 reviews the relevant articles. Section 3 presents the methods used in the paper. The conclusion is detailed in section 4, and section 5 presents future studies.

2. Literature Review

A review of research conducted on insolvency risk suggests numerous challenges in this field. A major area of this research is focused on the early prediction and detection of insolvency. Many models have been introduced for this purpose, such as CAMELS, Dynamic Detection, Z-score, Machine Learning, and SPC

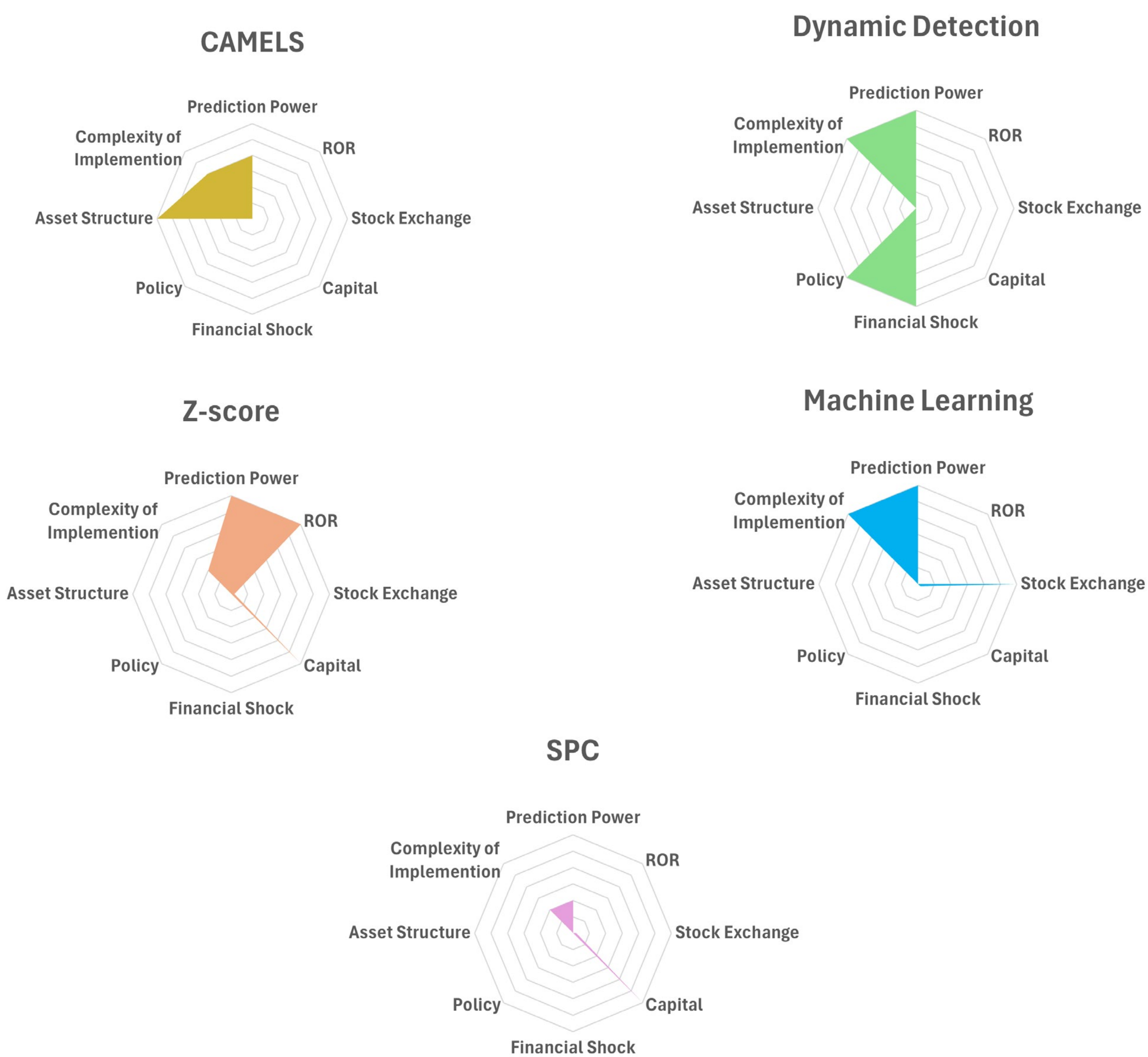

Figure 2. Insolvency detection methods (CAMELS, Dynamic Detection, Z-score, Machine Learning, and SPC)

Figure 2 compares the relevant papers based on the complexity of implementation (high, medium, and low), prediction power (high, medium, and low), and considered items in the method (stock exchange, capital, financial shock, policy, and asset structure)comparison based on complexity of implementation (high, medium, and low), prediction power (high, medium, and low), and considered items in the method (stock exchange, capital, financial shock, policy, and asset structure)

One of the models used for this purpose is machine learning (ML) techniques, which can effectively detect insolvency from unstructured data (De Jesus and da Nóbrega Besarria 2023). The Z-score is also one of the widely used indicators of insolvency (Lepetit et al. 2021; Mercadier and Strobel, 2024). Z-score measures the distance of the current state of a bank to insolvency. Time-varying-Z-Score and Altman's Z-Score are enhanced versions of Z-Score, which can examine the distance between a bank's current state and insolvency more effectively (Azam et al. 2023; Bouvatier et al. 2023).

Morgan Alexander Fox (2022) recognizes the CAMELS system as an efficient way to detect insolvency. Another explored model is Islamic banking (bin Md Nor et al. 2024). recognizes the principles of Islam and the challenges to a banking system through three stages of pre-insolvency, bankruptcy, and post-bankruptcy ,(bin Md Nor et al. 2024). Table 1 provides a detailed overview of relevant papers, comparing various methods in terms of case study, country, insolvency-related items, and methods A model that In the examination of insolvency, various factors can be named. Regulatory capital is an effective factor in causing bank insolvency risk (Conlon et al. 2020). Different types of regulatory capital are studied to understand their relationship with insolvency risk (Conlon et al. 2020). Findings suggest that there is a non-linear link between insolvency risk and capital components, indicating that low regulatory capital can cause an increasing bank insolvency risk (Conlon et al.2020). Furthermore, Unda and Ranasinghe (2021) explore the impact of board remuneration and corporate governance, drawing attention to theories such as the efficiency wage hypothesis, which investigates the relationship between insolvency risk and board pay structures.

Systemic risk and contagion are also two important factors in determining insolvency risk. Studies suggest that the interconnectedness of the financial network may lead to the transmission and amplification of shocks, causing systemic losses (Bougheas et al., 2024). Fire sales, which can cause a drop in the value of banking assets, are introduced to contribute to contagion across the banking system (Conlon et al. 2020).

Table 1. Relevant papers in comparison with the proposed model

References	Insolvency-related considered items	Case study	Country	Prediction	Methods				
					CAMELS	Dynamic model	Machine learning	Z-score	SPC
George G. Kaufman (2006)	Capital	✓	United States	-					
Thomas Conlon et al. (2020)	Capital	✓	Multiple countries	-				✓	
Laetitia Lepetit et al (2020)	Capital, ROR	✓	Multiple countries	✓					
James Nguyen et al. (2021)	Bank interest	✓	Multiple countries	-					
Michael Schillig (2021)	Policy and law	✓	Europe	-					
Luisa A. Unda et al. (2021)	Policy and Law	✓	Australia	-					
Marcelin, W. Sun et al. (2022)	Information sharing system, deposit	✓	Multiple countries	-					
Morgan Alexander Fox (2022)	Asset structure, capital stock	✓	Multiple countries	✓	✓				
Diego PittadeJesus et al. (2023)	Banks trade on the stock exchange.	✓	Brazil	✓			✓		
Vincent Bouvatier et al. (2023)	Capital, ROR	✓	Multiple countries	✓				✓	
Neeti Shikha (2023)	Capital	✓	Multiple countries	✓					
Arshe Azam et al. (2023)	Capital, ROR	✓	India	✓					
Spiros Bougheas et al. (2024)	Financial Shock	✓	United States	-					
Philipp J. König et al. (2024)	Policy and Law	-	-	-		✓		✓	
Rajib Shome et al. (2024)	Capital	-	-	-		✓			
Mathieu Mercadier et al. (2024)	Capital, ROR	✓	United States	✓				✓	
Ahmad Hidayat bin Md Nor et al. (2024)	Islamic Banking Policies	-	-	-					
Christoph Siebenbrunner et al. (2024)	Bail-ins	✓	Austria	✓					
This study	Capital	✓	Iran	✓					✓

Policy interventions and bank resolution are also addressed as consequential factors (König et al. 2024; Schillig, 2021). Michael Schillig (2021) suggests that harmonizing insolvency law in the EU can be particularly effective in the post-pandemic era. Other studies investigate the optimal timing of policymakers' intervention in situations such as the uncertain solvency of a bank (König et al. 2024). Emerging Studies explores the relationship between financial inclusion, information sharing, and bank risk-taking (Marcelin et al. 2022). This shows that in the absence of proper supervision, the bank risk can be increased (Marcelin et al. 2022). Neeti Shikha determines the effectiveness of supervision through the March 2023 bank failures of Silicon Valley Bank, Signature, and Credit Suisse.

The impact of bank diversification on profitability and insolvency risk is also analyzed, investigating the relationship between traditional banking income (net interest margin) and non-traditional income, and the effects of diversifying into off-balance sheet activities on risk-adjusted profits (Marcelin et al.2022). Post Gramm–Leach–Bliley Act studies are also investigated as an important factor in determining the effect of non-traditional banking activities on insolvency risk (Shome et al. 2025). As explained, various factors can be used to examine a bank's insolvency risk. One of the main explained factors is the relationship between capital and insolvency risk (Conlon et al.2020). Kaufman (2006) also investigates the relationship between insolvency and capital and introduces it as a leading factor. In this study, the insolvency of Iran's banks is examined through an analysis of required capital levels.

3. Methods

This study employs a quantitative approach that combines SPC methodologies with an analysis of efficient insolvency resolution processes in banking, focusing on the role of bank capital in these resolutions.
The study focuses on various banks, including ten prominent banks in Iran: Tejarat, Mellat, Pasargad, Saman, Ayandeh, Dey, Resalat, Saderat, Post Bank, and Eghtesad Novin. These banks were selected based on their market significance and the availability of comprehensive financial data. It has been ensured that a mix of banks with varying capitalization levels has undergone insolvency resolution processes

The data for this analysis were obtained from the official website of the Iranian Corporate Financial Reporting Database, accessible on the Codal website ("Codal,"), one of the most reliable Iranian websites regarding financial datasets. This platform provides access to the selected banks' financial statements, regulatory filings, and performance metrics. The data encompasses key required financial metrics for assessing capital ratios and evaluating the efficiency of insolvency resolutions, including balance sheets, income statements, and relevant notes to the financial statements of the banks listed.

The Total Capital Ratio (TCR) serves as a Capital Metric, and the time taken for resolution is used as an insolvency resolution indicator, forming the basic components of the framework.
The development of the SPC charts relies on three key components: sample groups, where data were collected from various operational metrics of the banks, including key capital ratios and other financial indicators; control limits, which were calculated from historical data and defined by upper control limits (UCL) and lower control limits (LCL); and the process mean, which serves as the central reference line on each chart. These limits help in assessing whether the process remains under control. The Lower Specification Limit (LSL) is also determined based on the minimum capital required to be released by the central bank. This amount is calculated for each year based on the future value of the most announced year, as the amount of capital needed is announced periodically. LSL was also adjusted by Consumer Price Index (CPI) in response to macroeconomic conditions.

The banks are grouped into 3 classes based on their capital amount. Small-capitalized banks are defined as those with total assets below 1,000 trillion IRR at the end of 2024. Medium-capitalized banks hold assets between 1,000 trillion and 5,000 trillion IRR, while well-capitalized banks exceed 5,000 trillion rials in total assets. Tejarat Bank, Pasargad Bank, Saderat Bank, and Melat Bank are considered well-capitalized banks. Ayandeh Bank, Eghtesadnovin Bank, Resalat Bank, and Saman Bank are grouped into the medium-capitalized banks class, and Dey Bank and Post Bank are considered as small-capitalized banks. These thresholds were determined by ranking all banks by total asset size and dividing the range into three groups with equal asset intervals.
The charts analyze include various capital ratios and insolvency indicators for the above-mentioned banks. The following findings were derived from the respective SPC charts.

Figure 3 indicates the status of well-capitalized banks. Although the figure reveals that the processes of all banks are statistically out of control, all the banks consistently remain above the LSL (Montgomery 2010). In this situation, operational irregularities are present, but the capital levels remain within an acceptable safety margin. This indicates that while traditional capital adequacy thresholds are met, systemic instability may still be present.

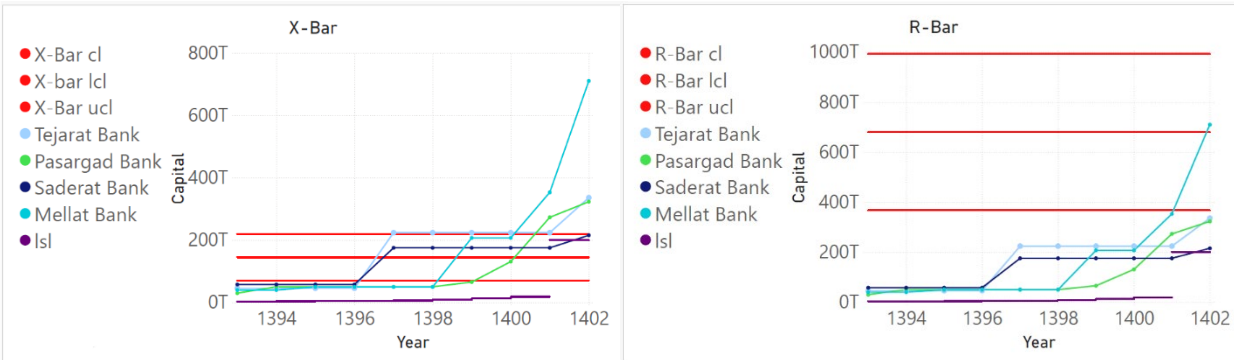

Figure 3 . X-bar and R-bar chart for the capital of well-capitalized banks (Tejarat, Pasargad, Saderat, and Melat Bank)

Figure 4 illustrates the control chart for medium-capitalized banks. Similar to the well-capitalized group, all banks in this category display statistically out-of-control processes (Montgomery, 2010). Notably, Ayandeh, Eghtesadnovin, and Resalt Bank fall below LSL at multiple points, signaling potential flaws in capital adequacy that increase the risk of insolvency. These flaws are critical early warnings that may reflect underlying weaknesses, such as poor capital management. However, Saman Bank, although also statistically unstable, remains consistently above the LSL, implying relatively stronger risk resilience. these patterns suggest the need for targeted intervention and closer monitoring of banks nearing capital thresholds, even when absolute failure has not yet occurred.

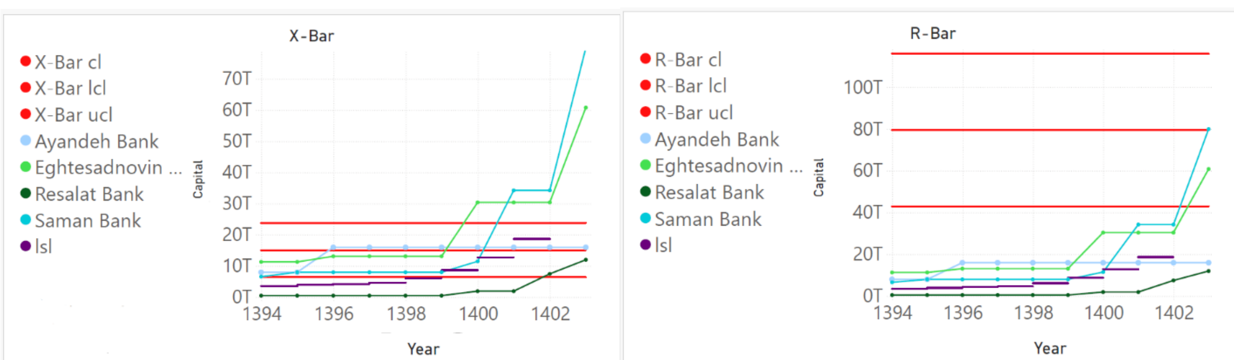

Figure 4. X-bar and R-bar chart for the capital of medium-capitalized banks (Ayandeh, Eghtesadnovin, Resalat, Saman Bank)

Figure 5 demonstrates the state of small-capitalized banks. Both banks in this group present statistically out-of-control processes (Montgomery, 2010). Within this group, Post Bank consistently falls below the Lower Specification Limit (LSL), highlighting a continuous failure to meet minimum capital requirements and signaling a high likelihood of insolvency if no corrective action is taken. In contrast, Dey Bank, while still statistically unstable, remains marginally above the LSL. This suggests a comparatively lower risk of insolvency, but systemic instability is still present. These findings emphasize the critical importance of continuous monitoring and early regulatory intervention in small-capitalize banks, which often operate with limited financial resilience and may be unable to manage rising operational and capital adequacy challenges.

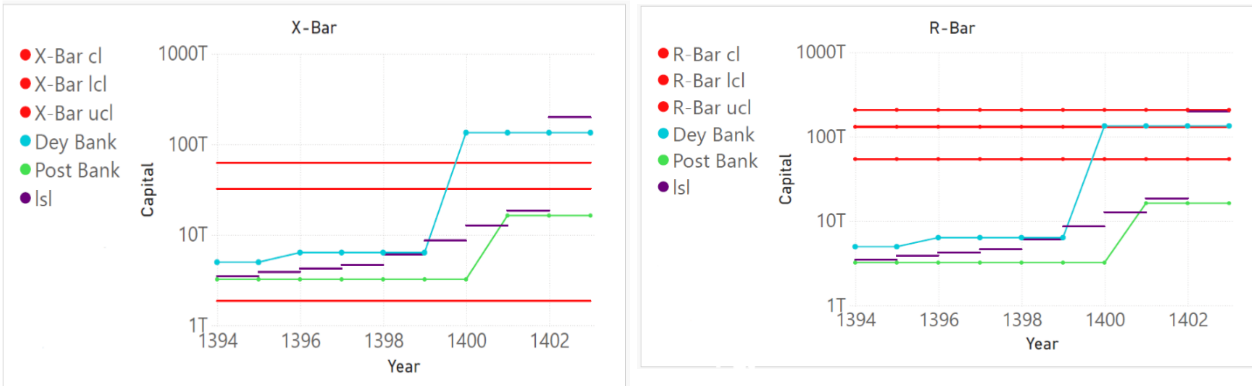

Figure 5. X-bar and R-bar chart for the capital of small-capitalized banks (Dey Bank and Post Bank)

4. Conclusion

The analysis of the SPC charts suggests that a robust monitoring system is crucial for identifying potential insolvency risks related to bank capital. Differentiating common cause and special cause variations enables bank management to address underlying issues proactively.

Banks should establish routine monitoring using SPC charts to ensure that capital ratios remain within control limits. Implement corrective actions immediately when trends indicate a deviation from control limits, particularly during periods of heightened variability.

Banks can also take Out-Of-Control Action Plans (OCAP) to avoid insolvency. OCAP is a flow chart that consists of corrective actions after an activity occurs (Montgomery and Runger, 2010). In an OCAP checkpoint, terminators are included to resolve out-of-control conditions. The first step of our OCAP is to check the data entry and the accounting equation. The accounting equation (Assets = Liabilities + Shareholders' Equity) controls whether the capital of the banks is compatible with shareholders' equity. The next step is to check whether the minimum amount of capital and the reporting time are set properly. During the establishment and capital registration process, banks are required to comply with customer identification and suspicious transaction reporting requirements to prevent any act of money laundering.. Therefore, the bank should control the requirements for combating money laundering in capital registration. Figure 6 suggests an OCAP to resolve the out-of-control condition of the 6 insolvent banks.

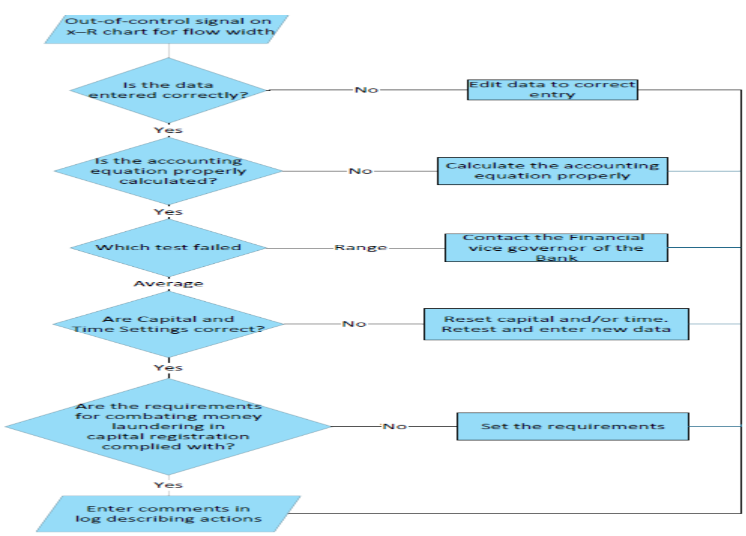

Figure 6. OCAP

Consider the underlying causes of any special variations in the process that may threaten the bank's capital stability. SPC charts are a powerful tool in assessing the efficiency of insolvency resolution processes and can aid in making informed decisions to maintain capital adequacy and financial health.In the context of emerging markets, the integration of SPC techniques into controlling frameworks offers a valuable opportunity. Regulators can adopt SPC-based early warning indicators to detect instability in banks' capital structures before traditional accounting signals emerge. This not only enhances oversight but also supports a more preventive and dynamic approach to financial regulation.

5. Future direction

While this study establishes a foundational SPC model focusing on bank capital, there remains substantial room for further investigation. Future research should expand the scope by incorporating additional factors influencing insolvency, such as rates of return, bail-in mechanisms, and asset structure. Additionally, long-term studies could examine the interactions between these variables and their collective impact on insolvency risk. Exploring the efficiency of incorporating machine learning techniques alongside SPC methods may further enhance predictive capabilities regarding bank stability. Such endeavors will contribute to a more comprehensive understanding of insolvency dynamics within the banking sector.

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