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THE LOAN-TO-DEPOSIT RATIO OF BANKS IN INTERACTION WITH INDICATORS OF OPERATIONS AND MACROECONOMIC INDICATORS - EVIDENCE FROM CROATIA

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Abstract

This paper examines the loan-to-deposit ratio (LDR) in the Croatian banking system from 2016 to 2025 and its relationship with operational efficiency (CIR), profitability (ROE), and macroeconomic conditions (GDP and CPI). LDR is considered a nonlinear, context-dependent mechanism linking funding structure, efficiency, and profitability. Using hierarchical clustering and an Adaptive Neuro-Fuzzy Inference System (ANFIS), the study identifies clear structural relationships: LDR is strongly connected with operational efficiency, ROE emerges as an intermediate outcome, while GDP and CPI constitute a separate macroeconomic dimension. The results indicate that high profitability occurs only under specific combinations of LDR, CIR, and stable macroeconomic conditions, whereas strong economic growth or higher inflation reduce efficiency and profitability. High CIR is identified as the main limiting factor. The findings suggest that bank performance depends on the interaction between internal and macroeconomic conditions in deposit-rich, bank-based economies.

Keywords: banks, loan-to-deposit ratio, banking and macroeconomic indicators, ANFIS

1. INTRODUCTION

The stability and efficiency of the banking system are a key prerequisite for sustainable economic growth, particularly in economies where banks represent the dominant channel of financial intermediation. One of the indicators that most accurately reflects the relationship between banks' lending activity and their capacity for stable funding is the Loan-to-Deposit Ratio (LDR). The LDR is defined as the ratio of total loans to total deposits on a bank's balance sheet, and its level is traditionally viewed as an indicator of the balance between profitable asset allocation and the preservation of banks' liquidity resilience.

As an aggregate indicator for the banking system as a whole, the LDR provides insight into the intensity of credit activity in the economy, the structure of funding sources, and banks' willingness to transform available deposits into loans. In both banking theory and practice, the LDR is assessed in the context of two key objectives: (i) revenue maximisation through credit expansion, and (ii) the maintenance of adequate liquidity in order to limit deposit withdrawal risk and ensure stable system functioning. Higher LDR levels are associated with stronger credit activity and potentially higher profitability, while lower levels indicate a more conservative lending policy, greater liquidity buffers, and lower risk exposure – albeit at the cost of a less efficient use of available funding sources.

Moreover, LDR dynamics at the level of the national banking system reflect broader macroeconomic developments. A rising LDR often signals increased bank optimism and stronger credit support to the real sector, typical of economic expansion phases, whereas a declining LDR points to reduced risk appetite, deposit accumulation during periods of heightened uncertainty, or subdued credit demand. Beyond cyclical trends, the LDR also serves as an indicator of the structural characteristics of the financial system, including reliance on domestic deposits versus foreign funding sources, banks' capacity to generate sustainable credit growth, and their vulnerability under conditions of financial stress.

In the context of transition and small open economies, such as Croatia, the LDR is of particular relevance. Historically elevated LDR levels in the pre-crisis period of the 2000s reflected strong credit expansion driven largely by foreign funding, while the aftermath of the global financial crisis was characterised by a prolonged period of subdued lending activity and a growing deposit base, resulting in a pronounced decline in the ratio. In more recent years, Croatia has again experienced an increase in the LDR; however, this development has been underpinned by a significantly stronger reliance on domestic deposits and has taken place within a fundamentally different regulatory and risk-management environment than prior to 2008. This shift is closely related to the emergence of a "new non-standard ecosystem" shaped by the single monetary policy now conducted by the European Central Bank, alongside a persistently elevated and resilient inflation environment.

Accordingly, the primary goal of this empirical study is to investigate the interaction between credit-deposit activity (LDR), bank performance and macroeconomic dynamics in Croatia. By applying a non-linear approach, the paper seeks to identify potential behavioral regimes that traditional analysis might obscure. Given the relatively limited sample size, the results should be interpreted as exploratory rather than definitive evidence.Within this framework, the key questions concern the extent to which changes in the LDR in Croatia can be interpreted as signals of cyclical developments, how far they reflect adjustments in banks' business models, and whether a clear relationship exists between the LDR, banking sector performance, and broader macroeconomic indicators. This paper contributes to the empirical literature by providing a detailed analysis of these relationships, using advanced nonlinear modeling to better understand the dynamics of the Croatian banking system within a specific macroeconomic context.The paper addresses the following research questions:

1. What is the empirical structure of the relationship between banking indicators (LDR, CIR, ROE) and macroeconomic variables (GDP, CPI) over the period 2016–2025?
2. To what extent do nonlinear patterns and distinct "regimes" exist in the relationships between banking and macroeconomic variables provide a more granular view of bank profitability (ROE)?
3. How does the macroeconomic environment (GDP, CPI) modify the relationship between funding structure and lending activity (LDR) and operational efficiency (CIR), and how do these interactions affect the overall performance of the banking system (Basel III)?

2. LITERATURE REVIEW

The loan-to-deposit ratio (LDR) has been extensively examined in the academic literature as a key indicator of banks' liquidity transformation, funding structure, and exposure to imbalances in the credit intermediation process. A substantial body of research emphasises that the LDR reflects not only banks' internal behaviour but also broader macro-financial conditions, including monetary policy transmission, credit cycles, and economic growth. Both theoretical and empirical strands of the literature highlight the LDR as one of the central indicators of banks' funding structure and their ability to maintain liquidity.

Classical contributions to the theory of financial intermediation, most notably Diamond and Dybvig (1983), underscore the necessity for banks to balance maturity transformation against the risk of deposit withdrawals, thereby rendering ratios such as the LDR important signals of financial stability. In more recent studies, the LDR has increasingly been analysed within the broader framework of liquidity regulation, alongside measures such as the Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR), which were

introduced under the Basel III regulatory framework (Basel Committee on Banking Supervision [BCBS]; BCBS, 2013; BCBS 2019). Empirical studies (Demirgüç-Kunt & Huizinga, 2010; Ozili, 2019) show that higher LDR levels are associated with greater bank profitability, but also with elevated credit and liquidity risk, as well as potential deterioration in asset quality. More recent analyses (Mirzaei & Moore, 2021) suggest a nonlinear, inverted U-shaped relationship between the LDR and bank profitability, whereby moderate increases in the LDR enhance returns, while excessively high values signal potential vulnerability.

The LDR is conceptualised as a structural liquidity metric indicating the extent to which banks finance their loan portfolios through stable deposit funding rather than non-deposit or market-based sources (Dinger, 2009; Bonner & Eijffinger, 2015). High LDR levels are often correlated with increased liquidity pressures, heightened vulnerability to funding shocks, and greater sensitivity to monetary tightening (Disyatat, 2011; Brunnermeier & Oehmke, 2013). Empirical evidence further suggests that banks with persistently high LDRs face elevated liquidity stress risks during periods of market turbulence (Cornett, McNutt, Strahan, & Tehranian, 2011). A substantial body of empirical literature examines the dual effect of the LDR on bank profitability. On the one hand, higher LDR levels may indicate a more efficient use of deposits in generating interest income, thereby enhancing profitability as measured by ROA and ROE (Pasiouras & Kosmidou, 2007; Athanasoglou, Brissimis & Delis, 2008; Radovanov, Dragosavac & Marcikić, 2023).

On the other hand, an excessively high LDR may lead to increased funding costs, particularly when banks are required to compensate for deposit shortfalls through market-based funding sources (Heider & Hoerova, 2018). Such conditions may adversely affect the cost-to-income ratio (CIR). In addition, excessive reliance on lending relative to deposit funding heightens liquidity and credit risk, which in turn tends to reduce profitability during economic downturns (Iannotta, Nocera & Sironi, 2007; Berger & Bouwman, 2009). Moreover, several studies document a nonlinear effect, whereby profitability increases with the LDR up to a certain threshold, beyond which it declines (Dietrich & Wanzenried, 2011; Tran, 2020). These nonlinearities suggest that the marginal impact of LDR is not constant, justifying a move from general linear estimates to regime-oriented methodologies like ANFIS, which can capture local variations in data structure that are often lost in aggregated OLS models.

Analyses conducted by central banks also highlight the trade-off between profitability and liquidity. The European Central Bank (ECB) finds that euro area banks with more balanced loan and deposit structures exhibit stronger and more stable net interest margins, particularly in low interest rate environments (ECB, 2016). Similarly, the U.S. Federal Reserve (FED) shows that banks with moderate LDR levels display more resilient earnings performance and lower crisis-related losses (FED, 2017). The macroeconomic literature links LDR behaviour to broader credit supply conditions and the dynamics of the real

economy. High LDR levels typically accompany strong credit booms, which may amplify economic expansions but also increase systemic risk (Schularick & Taylor, 2012). By contrast, low LDR levels signal conservative lending positions or weak credit demand, potentially constraining economic activity (Jorda, Schularick & Taylor, 2016). Evidence from emerging markets indicates that LDR tightening is often associated with the transmission of monetary policy through the bank lending channel (Nguyen & Boateng, 2013). In economies that rely heavily on the banking sector – such as euro area member states and Croatia – the credit channel represents the dominant mechanism through which financial conditions are transmitted to the real economy (Pagano & Langfield., 2014; European Banking Authority [EBA], 2023).

An increase in the LDR implies more intensive credit growth, which in the short run stimulates economic activity, particularly in sectors that are highly dependent on external financing (Beck, Degryse & Kneer, 2018; Shijaku, 2020). However, the literature cautions that excessive credit growth may generate financial imbalances, especially in real estate markets and highly leveraged sectors, thereby increasing the economy's vulnerability to crises in the long run (Borio & Lowe, 2002). Consequently, the impact of the LDR on economic growth is viewed as twofold: positive through the stimulation of investment and consumption, and negative if rising financial risk leads to a deterioration in credit portfolio quality. This insight is particularly relevant for Croatia, where banks play a central role in financing the private sector, and where historically low LDR levels point to significant unused potential for stronger credit support to economic growth.

Recognising these macroprudential implications, the European Banking Authority (EBA) and the European Securities and Markets Authority (ESMA) emphasise monitoring LDR dynamics as part of systemic risk dashboards, particularly in the assessment of funding risks and patterns of credit expansion across EU Member States (EBA, 2020). In the post-2008 period, comparative research has identified a divergence in LDR developments between advanced and emerging financial systems. Studies show that euro area peripheral countries experienced elevated LDR levels prior to the crisis, which contributed to amplified credit cycles (Lane & McQuade, 2014; Merler & Pisani-Ferry, 2012). By contrast, banking systems characterised by a deposit-based funding culture – such as those in parts of Central and Eastern Europe, including Croatia – maintained lower and more stable LDR levels, thereby enhancing resilience (Derviz & Podpiera, 2010). Post-crisis literature further highlights the role of prudential regulation in constraining excessive growth in LDR levels.

The BIS, ECB, EBA, and the FED emphasise the LDR as an important—though not formally regulated – macroprudential indicator linked to systemic liquidity buffers and the sustainability of bank funding structures. From a regulatory perspective, the Bank for International Settlements (BIS) underscores the importance of stable funding as a counterbalance to maturity transformation, noting that excessive credit growth relative to deposit bases was a key driver of

financial vulnerabilities prior to 2008 (BIS, 2010). Although the Basel III framework does not directly regulate the LDR, it implicitly constrains it through the NSFR and the LCR (BCBS, 2014). Within the regulatory literature, key institutions systematically monitor and interpret the LDR.

The European Central Bank (ECB, 2023; ECB, 2024) uses the LDR as an indicator of credit activity and deposit structure in European banks, emphasising that it must be interpreted jointly with measures of liquidity resilience. The ECB highlights the composition and stability of funding sources as a key indicator of banks' vulnerability. Particular attention is paid to reliance on safe and stable funding sources – primarily household and corporate deposits – relative to more volatile market-based (wholesale) funding (ECB, 2016). In the post-crisis period, a decline in reliance on wholesale funding and an increase in the share of deposits in total bank liabilities have been observed, which the ECB interprets as evidence of strengthened sustainability of banks' business models (ECB, 2016). This trend has been accompanied by a declining LDR, viewed as an indicator of reduced funding risk.

The LDR is one of the key indicators of a bank's ability to finance its lending activity internally – through deposits – rather than relying on external funding sources. The ECB stresses that an excessively high LDR signals vulnerability under conditions of market stress, while an excessively low LDR may indicate inefficient allocation of funds and a weaker contribution of bank lending to economic activity (ECB, 2023). In periods of monetary regime shifts, particularly during the inflationary environment of 2021–2024, the value of the deposit franchise becomes crucial for containing funding costs and preserving profitability and margin stability (ECB, 2025). As a result, the LDR is increasingly assessed in regulatory and supervisory contexts in conjunction with net interest income and ROA/ROE indicators. The ECB further emphasises that changes in banks' funding conditions are directly reflected in credit supply, the cost of capital, and overall economic activity and investment. In this way, the LDR is confirmed as an integral link between banks' business stability, profitability, and the broader macroeconomic environment – making it a relevant indicator in assessments of financial stability and the macroeconomic cycle. Furthermore, the FED (2023; 2024), in its supervisory reports, highlights that increases in the LDR may reflect declining deposit volumes, rising lending activity, or a combination of both processes, particularly in an environment of volatile interest rates.

The BCBS (2013; 2019) does not formally include the LDR as a regulatory standard, but emphasises that the LCR and NSFR are designed to address precisely the risks implied by the LDR - namely refinancing risk and structural liquidity risk. The EBA (2021; 2022; 2023; 2024), in its liquidity risk assessments, analyses the role, composition, and stability of deposits, emphasising that the LDR can provide valuable information when combined with regulatory liquidity metrics. Although primarily focused on capital markets, the ESMA (2023) also points to related liquidity risks among entities with credit

exposures – such as loan-originating alternative investment funds – thereby further underscoring the importance of structurally monitoring the relationship between lending activity and funding sources. In the context of Croatia, this research builds on the scarce domestic literature on LDR. The ANFIS model confirms the theses of Benazić and Učkar (2024) about the macroeconomic determinism of credit, while the nonlinear pressures on CIR coincide with the analysis of monetary contraction by Levaj and Viljevac (2025). In Croatia, LDR therefore appears as a dynamic category conditioned by the economic cycle and the transmission of monetary policy measures.

Although studies such as those by Dietrich and Wanzenried (2011) and Mirzaei and Moore (2021) confirm the nonlinearity in the liquidity-profitability relationship, traditional econometric models (such as OLS) have difficulty capturing complex, overlapping „if-then“ regimes. In contrast, ANFIS combines the learning ability of neural networks with the interpretability of fuzzy logic, allowing the identification of „behavioral regimes“ without predefined thresholds. This is particularly important for transition economies such as Croatia, where structural breaks are common. The choice of ANFIS directly responds to the literature on the „trade-off“ between liquidity and profitability (ECB, 2023). While linear models offer only average performance, ANFIS explains why the same parameters (e.g. LDR) result in different outcomes under the influence of inflation or efficiency (CIR). This approach maps theoretical trade-offs onto a multidimensional „risk/return surface“, providing more granular insight than conventional estimates. Nevertheless, machine-learning approaches may face limitations in small macro-financial samples, including sensitivity to model specification and potential overfitting, which requires careful validation.

3. DATA DESCRIPTION AND METHODOLOGY

Based on available data from the Croatian National Bank (CNB), an empirical analysis of the loan-to-deposit ratio (LDR) in the Croatian banking system over 37 quarters in the 2016–2025 period reveals a marked decline in the LDR after 2018, primarily driven by strong growth in household and non-financial corporate deposits, alongside a simultaneous moderate expansion of lending activity.

During the pandemic period and immediately thereafter, the LDR fell below 70%, indicating the accumulation of excess liquidity and increased risk aversion among banks. The lowest level of the LDR was recorded at the end of 2022, confirming a weakening of the credit transmission channel to the real sector. From 2023 onwards, a gradual increase in the LDR has been observed, driven by an acceleration in lending and a slowdown in deposit growth (Appendix, Figure 6).

Nevertheless, despite the recovery, the LDR remains well below historical levels and the EU average, pointing to a persistently conservative

funding structure of the Croatian banking system. A comparison of the Croatian LDR with the average LDR of the EU-27 (EBA, 2025) clearly shows that Croatia has maintained a significantly lower LDR than the EU-27 average throughout the entire 2016–2025 period (Appendix, Figure 7). This comparison suggests that the Croatian banking system exhibits a structural liquidity surplus and a relatively low degree of financial intermediation compared to the EU. Such a ratio reduces profitability (through lower interest income) but enhances the system's resilience to liquidity stress and confidence crises. Moreover, in terms of GDP growth, a lower LDR may imply a weaker transmission of the credit channel of monetary policy, i.e. a smaller contribution of bank lending to overall economic activity.

Such dynamics allow for further analysis of the interaction between the LDR and operational efficiency (CIR), profitability (ROE), and macroeconomic conditions (GDP, CPI), and provide justification for the application of nonlinear models such as ANFIS. The methodological approach and the rationale for applying hierarchical clustering and ANFIS are based on the observed variables presented in Table 2 over the period from 2016 to 2025 (Appendix, Table 2). The variables are described below:

LDR (Loan-to-Deposit Ratio**)** – the ratio of loans to deposits; defined as the ratio of total loans to total deposits on a bank's balance sheet.

ROE (Return on Equity) – a measure of profitability; used in this study as one of the key indicators of banks' business performance.

CIR (Cost-to-Income Ratio) – the ratio of costs to income; an indicator of operational efficiency (a lower CIR generally implies higher operational efficiency).

GDP (Gross Domestic Product) – a macroeconomic indicator of the level and pace of economic activity and growth.

CPI (Consumer Price Index) – a macroeconomic indicator of inflation, reflecting changes in the general price level.

The analytical framework combines two complementary methods in order to examine the relationships between banking indicators (LDR, CIR, ROE) and macroeconomic variables (GDP, CPI) in a manner that is both empirically grounded and interpretable. Hierarchical clustering is first employed as an exploratory step to identify latent structures and natural groupings among the variables, after which ANFIS is applied to model the nonlinear relationships and interactions that are characteristic of financial and macroeconomic systems (Brlečić Valčić, S., Peša, A. & Čičin-Šain, D. 2025).

Both analyses were conducted using the MATLAB software environment, with all variables standardized in advance using Z-scores to ensure comparability and to mitigate the influence of differing measurement scales on distance calculations and model learning (Everitt, B. S., Landau, S., Leese, M., & Stahl, D., 2011; Jain & Dubes, 1988). Hierarchical clustering was selected because it is particularly suitable for empirically identifying variables that share similar dynamics and for representing these similarities within a hierarchical

structure without requiring an a priori specification of the number of clusters (Everitt et al., 2011; Kaufman & Rousseeuw, 1990).

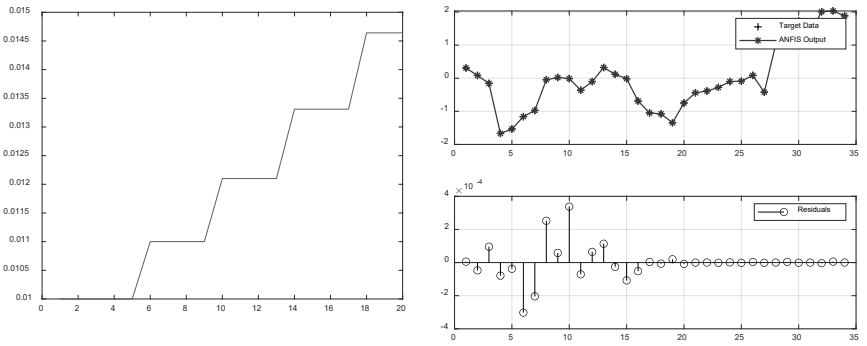
In the context of this study, the dendrogram served as a „conceptual map" indicating the clustering of banking variables (e.g. LDR–CIR), the distinct role of ROE, and a separate macroeconomic layer (GDP–CPI). This structure is highly relevant for subsequent modeling, as it suggests which interactions are potentially the most economically meaningful. In MATLAB, this procedure was operationalized using the *linkage* function with average linkage and visualized through a dendrogram constructed on standardized data (The MathWorks, Inc., n.d.). ANFIS (Adaptive Neuro-Fuzzy Inference System) was selected because it enables the simultaneous (i) approximation of complex nonlinear functions and (ii) preservation of interpretability through fuzzy rules, which is particularly valuable in economic and financial analyses where regime-dependent behavior is expected (e.g., „high LDR + medium CIR → high ROE"), rather than constant marginal effects.

Conceptually, the method builds on fuzzy set theory (Zadeh, 1965) and Takagi–Sugeno fuzzy models (Takagi & Sugeno, 1985), while ANFIS formally introduces neuro-adaptive learning of the parameters of the fuzzy system (Jang, 1993). In this study, ANFIS was applied to further investigate, through nonlinear interactions with macroeconomic conditions, the relationships that hierarchical clustering indicated as structurally linked. Two models were trained in MATLAB: Model 1 (inputs: LDR, CIR, GDP, CPI; output: ROE) with 81 fuzzy rules and a minimum training RMSE of 0.000104467, and Model 2 (inputs: LDR, GDP, CPI; output: CIR) with 27 fuzzy rules and a minimum training RMSE of 0.0411879. The implementation and training of ANFIS relied on MATLAB's neuro-adaptive learning capabilities and the ANFIS functionalities within the Fuzzy Logic Toolbox (The MathWorks, Inc., n.d.). To reduce model complexity, the number of membership functions and fuzzy rules was selected iteratively based on validation performance rather than maximum fit.

The characteristics of ANFIS Model 1 and ANFIS Model 2 are presented in Figure 1 and Figure 2, respectively.

ANFIS 1 info:
Number of fuzzy rules: 81
Minimal training RMSE = 0.000104467

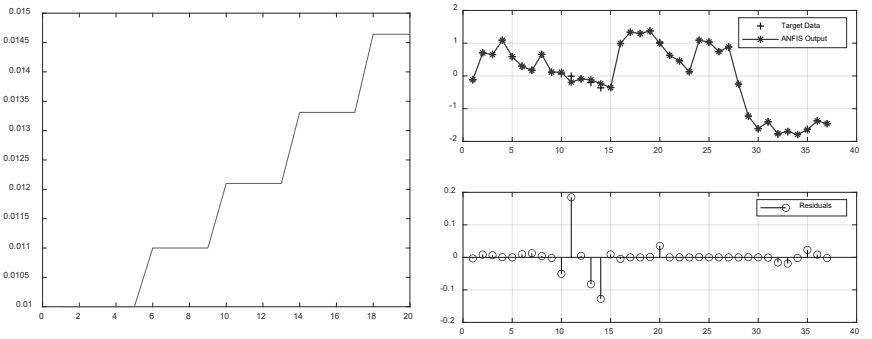
Figure 1 Training characteristics and relationships among the trained variables of the ANFIS Model 1



Source: Prepared by the authors using the MATLAB software package

ANFIS 2 info:
Number of fuzzy rules: 27
Minimal training RMSE = 0.0411879

Figure 2 Training characteristics and relationships among the trained variables of the ANFIS Model 2



Source: Prepared by the authors using the MATLAB software package

To ensure that the identified nonlinear relationships were not merely a result of overfitting to sample-specific characteristics, an additional assessment of the stability and robustness of the results was conducted. All data were standardized (Z-score) prior to analysis to ensure comparability of variables, with standardization implemented in a manner that minimizes potential bias in model estimation (standardization parameters were calculated on the training data and subsequently applied to the remaining datasets). The ANFIS models were estimated in MATLAB while simultaneously monitoring both training and

validation errors, allowing for control of overfitting and preservation of the models' generalizability.

Out-of-sample validation was performed respecting the temporal ordering of observations (walk-forward/rolling approach), such that the model was iteratively trained on an earlier portion of the period and evaluated on the subsequent available period. Model performance was assessed using standard error metrics (primarily RMSE, with supplementary MAE), and robustness was further tested by comparing specifications of differing complexity (varying numbers of fuzzy rules) and benchmarking against a simpler reference model.

To provide additional indicative support for the nonlinear approach, the predictive performance of the ANFIS model was compared with a reference linear regression model using the same input variables. The comparison showed that ANFIS achieved lower prediction errors (RMSE and MAE), suggesting that nonlinear modeling provides additional explanatory value compared to standard linear specifications.

Table 1 Benchmark comparison

Model	Evaluation Metric	Reference Linear Model (OLS)	ANFIS Model
Model 1 (Output: ROE)	RMSE	1.5863	0.0001
Model 2 (Output: CIR)	RMSE	4.7456	0.0412

Note: OLS results obtained via EViews; ANFIS results obtained via MATLAB.

Source: Author's calculations

RMSE was selected as the primary evaluation metric because it provides a more rigorous assessment by penalizing larger errors more heavily than MAE. This is particularly relevant in financial modeling, where minimizing significant deviations is crucial for model reliability. These findings suggest that the relationships between macroeconomic indicators and banking performance metrics are inherently nonlinear and complex. While a linear model captures only broad average trends, the neuroadaptive learning capability of ANFIS allows it to map complex nonlinear interactions that traditional econometrics may overlook.

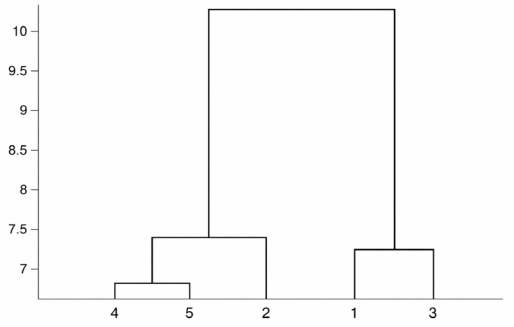
The relationships identified in this way with respect to the profitability and efficiency of Croatian banks are of a research and methodological nature, dependent on the sample, and are indicative, within the regulatory framework after 2016.

4. RESEARCH RESULTS AND DISCUSSION

Over the period 2016–2025, hierarchical clustering of the observed variables (Table 2, Figure 3) resulted in a three-cluster structure, indicating a clear differentiation between the banking-operational dimension (LDR and CIR),

profitability (ROE), and the macroeconomic environment (GDP and CPI). This configuration aligns well with the conceptual framework, in which the LDR serves as an aggregate indicator simultaneously reflecting the intensity of lending, the structure of funding sources, and the trade-off between profitable lending and the liquidity resilience of banks.

Figure 3 Results of hierarchical clustering of the observed variables



Source: Prepared by the authors using the MATLAB software package

The strongest link was identified within the LDR–CIR cluster, suggesting that during the observed period, changes in the LDR most directly "translate" through the dimension of operational efficiency and cost pressures. The theoretical literature emphasizes that a higher LDR may signal increased lending activity and potentially higher profitability, but it can simultaneously raise the need for alternative (market-based) funding sources if the deposit base does not keep pace with credit growth. This channel increases funding costs and may worsen the cost-to-income ratio (CIR), which explains why their joint clustering is theoretically expected. The ROE variable forms a separate cluster but is hierarchically linked to the LDR–CIR cluster, indicating that profitability functions as an „intermediate" outcome that integrates the simultaneous effects of funding structure and operational efficiency.

Previous studies explicitly highlight the dual effect of LDR on profitability: moderate increases in LDR can support ROE through more effective use of deposits to generate interest income, whereas excessively high LDR levels can reduce ROE by raising funding costs, liquidity and credit risk, and deteriorating CIR. This nonlinear logic helps explain why ROE does not cluster directly with LDR or CIR but appears separately, while still being connected in the hierarchical structure.

The third cluster comprises GDP and CPI, confirming that the observed macroeconomic indicators share a common component of the economic cycle and the inflationary environment. Their hierarchical linkage to ROE suggests that, during the observed period, macroeconomic changes are most directly reflected in

profitability (e.g., through financing conditions, interest margins, and costs) and only subsequently influence relationships among banking indicators indirectly.

This finding is consistent with the earlier argument that LDR dynamics at the banking system level should be interpreted in interaction with economic growth and inflation, positioning LDR as an "integrative nexus" connecting bank stability, profitability, and the broader macroeconomic environment. Overall, the resulting cluster structure supports the interpretation that in the Croatian context, LDR is primarily associated with the cost-operational dimension (CIR), while its effects on profitability (ROE) materialize through the combined influence of funding structure and operational efficiency.

The macroeconomic environment (GDP and CPI) constitutes a separate yet relevant layer, most clearly reflected in profitability outcomes. This finding further reinforces the central research premise of this study: changes in the LDR should not be considered in isolation but rather as part of a broader interaction between banking performance and macroeconomic conditions. Based on the findings outlined above, a further analysis was conducted using two ANFIS models.

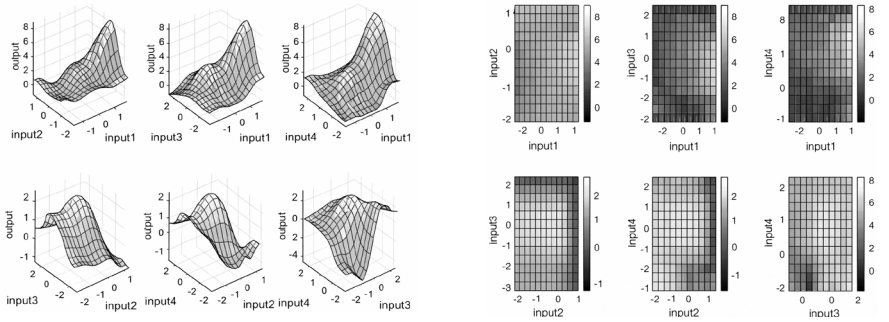
4.1. ANFIS Model 1: Profitability as the Output (Integrated Model)

Purpose: ROE is modeled as an aggregate outcome of banking and macroeconomic conditions, consistent with its hierarchical linkage to both the LDR–CIR cluster and the GDP–CPI cluster.

- Inputs (X):
  1. LDR (loan-to-deposit ratio)
  2. CIR (cost-to-income ratio)
  3. GDP (gross domestic product)
  4. CPI (consumer price index)
- Output (Y): ROE (return on equity)

This model directly operationalizes the finding that ROE occupies an intermediate position between the banking and macroeconomic clusters.

Figure 4 Results of ANFIS Model 1 in 3D and 2D representations



Source: Prepared by the authors using the MATLAB software package

The results of ANFIS Model 1 (Figure 4) clearly illustrate that profitability (ROE) is a nonlinear function of the simultaneous influence of banking and macroeconomic factors, with the „optimal profitability regime“ occurring only under specific combinations of inputs. The most pronounced finding relates to the interaction between LDR and CIR: very high LDR values combined with moderate CIR levels generate very high ROE, whereas all other combinations predominantly result in medium or low ROE. This pattern indicates that increased lending activity and more intensive utilization of the deposit base (high LDR) translate into profitability only when operational efficiency is maintained (CIR is not elevated). Conversely, a scenario with a moderate LDR and very high CIR is associated with very low ROE, suggesting that operational inefficiency can outweigh the potential benefits of lending activity and strongly constrain return on equity.

Additionally, the ANFIS model shows that the effect of LDR on ROE depends on the macroeconomic context, with „very high ROE“ emerging in combinations of very high LDR with moderate GDP values, as well as very high LDR with moderate CPI values. This implies that achieving the highest profitability is more favorable under a moderately stable macroeconomic environment than during extreme cyclical conditions. Notably, very low ROE is predicted for combinations of either very low or very high LDR with very high GDP, pointing to the existence of „adverse extremes“ in funding/lending strategy under conditions of exceptionally strong growth. This result can be interpreted as a signal that extremely high LDR during a phase of strong economic expansion may increase vulnerability (e.g., through funding costs or risks), while extremely low LDR may indicate missed profit opportunities and weaker monetization of economic momentum.

In comparison, the interactions involving CIR further confirm that operational efficiency is a key prerequisite for profitability: high ROE values occur at moderate CIR levels combined with moderate GDP values, as well as

moderate CIR levels combined with moderate CPI values, whereas very high CIR produces extremely low ROE across almost all GDP and CPI levels (particularly when GDP is low). This positions CIR as a dominant „brake“ capable of neutralizing the positive effects of lending activity and a favorable macroeconomic environment. Finally, the GDP–CPI macroeconomic interaction suggests that higher ROE is more likely under moderate-to-high GDP levels across a wide range of CPI values, while the combination of low GDP and low CPI systematically corresponds to very low ROE. This finding is consistent with an environment of weak economic dynamics and less favorable conditions for generating returns.

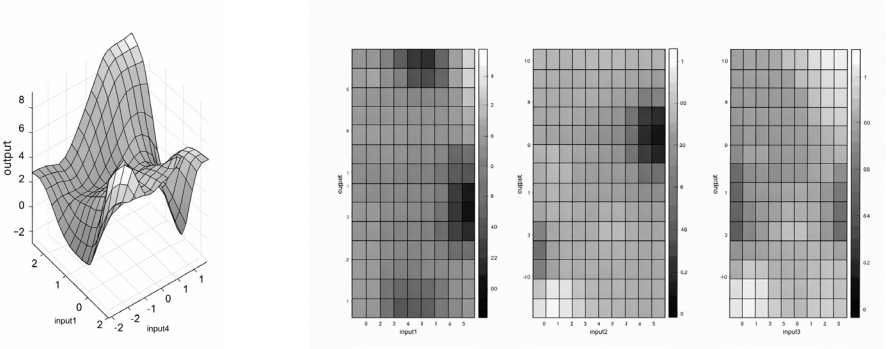
4.2. ANFIS Model 2: Operational Efficiency as the Output (Banking-Cluster Channel)

Purpose: To isolate the closest relationship identified in the clustering (LDR–CIR) and examine how CIR is determined in the context of macroeconomic conditions (GDP, CPI).

- Inputs (X):
  1. LDR
  2. GDP
  3. CPI
- Output (Y): CIR

This model encompasses the LDR–CIR cluster, with the macroeconomic variables acting as the surrounding context that can amplify or dampen this relationship.

Figure 5 Results of ANFIS Model 2



Source: Prepared by the authors using the MATLAB software package

The results of ANFIS Model 2 (with CIR as the output and LDR, GDP, and CPI as inputs), presented in Figure 5, indicate that the operational efficiency of the banking system (CIR) does not behave linearly but depends on specific combinations of funding/lending structure (LDR) and the macroeconomic regime (GDP, CPI). The derived rules imply the existence of „cost-pressure regimes" and „efficiency regimes", with extreme CIR values associated with extreme combinations of banking and macroeconomic variables. In the LDR–GDP interaction, it is evident that very high CIR values primarily occur in scenarios combining very high LDR with very high GDP. This pattern can be scientifically interpreted as indicating that during periods of exceptionally strong economic growth, when lending activity is aggressive (high LDR), cost burdens relative to income tend to rise.

This may indicate increased funding costs (if the deposit base does not keep pace with credit growth), higher risk management expenses, faster business expansion and associated infrastructure costs, or operational pressures linked to intensified lending activity. Conversely, the model suggests that very low CIR values arise under very high LDR combined with low-to-moderate GDP, indicating that in more moderate cyclical conditions, banks are able to achieve lending volumes while maintaining a relatively favorable cost-to-income balance-that is, credit expansion can be converted into income without a proportional increase in costs.

The interaction between LDR and CPI further confirms the „regime-dependent" nature of efficiency. The finding that low LDR values combined with low CPI values result in a high CIR can be interpreted as a situation where credit activity is weak (lower LDR) and inflation is low, which may be associated with limited revenue dynamics and weaker balance sheet monetization, while fixed or slowly adjustable operating costs increase relatively compared to revenues. Conversely, very low CIR values occur in two extreme scenarios: (i) very low LDR with low to medium CPI values, and (ii) very high LDR with high CPI values.

The first scenario may reflect periods in which banks, under extremely conservative lending, achieve relative cost „compression" (e.g., cost restructuring, operational streamlining), whereas the second scenario may imply that in conditions of elevated inflation, credit activity and revenues grow sufficiently to improve the cost-to-income ratio, even if nominal costs increase. At the GDP–CPI level, the combination of variables further suggests that high CIR values are associated with „extreme macro regimes", meaning that heightened cost pressures appear when both GDP and CPI are very low, as well as when both GDP and CPI are very high. The first case may represent an unfavorable environment of weak economic activity and low inflation, where bank revenues are muted, causing CIR to rise due to a relatively high cost burden.

The second case may indicate an overheated economy with simultaneously strong growth and inflation, where costs (e.g., labor, process compliance, risk management, and funding) rise rapidly and may offset revenue growth. Additionally, the observation that very low CIR values appear under low

GDP with medium CPI, and under very high GDP with medium CPI, suggests that „stable“ inflation (medium CPI) may act as a condition facilitating more efficient cost management at different stages of growth, whereas inflation extremes (very low or very high CPI) are more likely to amplify cost pressures.

Overall, ANFIS Model 2 provides a scientifically relevant insight that CIR during the observed period is shaped by the interaction effect of banking strategy (LDR) and the macroeconomic regime (GDP and CPI), with extreme CIR values most often associated with extreme cyclical combinations. This finding is important because it implies that banking system efficiency is not a stable characteristic, but varies depending on whether the system operates under a regime of weak growth and low inflation or under a regime of very strong growth and high inflation, and on how credit activity (LDR) is positioned within those regimes. This interpretation also strengthens the argument of this study that the relationships among LDR, CIR, and profitability should be analyzed nonlinearly and contextually, rather than through equations with constant marginal effects.

Although the LDR is the primary indicator of this paper, its results are closely related to the Basel III standards (LCR and NSFR). The identified nonlinear regimes, in which high LDR under macroeconomic pressures (CPI/GDP) affects efficiency, correlate with the efforts of the EBA and ESRB in mapping systemic risks. The high levels of LCR in Croatian banks (above 100%) explain the resilience of the system even with elevated LDR. While the LCR focuses on short-term resilience, our analysis of the interaction of the deposit base and credit mirrors the logic of the NSFR - a stable funding structure allows for higher LDR without compromising compliance. Therefore, the LDR serves as a potentially important early indicator in supervisory „heat maps“, signaling possible deviations from Basel III standards before their formal materialization.

5. CONCLUSION

This exploratory empirical study starts from the premise that the LDR in the Croatian banking system is a suitable aggregate indicator that simultaneously reflects lending intensity, funding structure, and the trade-off between profitability and liquidity resilience, with its interpretative value increasing when considered alongside bank performance indicators (ROE, CIR) and the macroeconomic environment (GDP, CPI). The analysis for the period 2016–2025 suggests that the relationships among the observed variables are neither linear nor reliably interpretable in isolation, but are strongly nonlinear and context-dependent, which is consistent with the framework outlined in the accompanying document emphasizing the need to consider both banking performance and macroeconomic developments when interpreting LDR.

Regarding the first research question on the structure of the relationships between banking and macroeconomic variables, hierarchical clustering revealed a clear three-cluster hierarchy: LDR and CIR are most closely related (bank-

operational dimension), followed hierarchically by ROE as a separate profitability variable, while the macroeconomic variables GDP and CPI form a distinct cluster. This structure suggests that changes in LDR over the observed period are reflected in operational efficiency (CIR), while the macroeconomic component is grouped separately, but its impact on the system is most clearly reflected in profitability (ROE). This further confirms the role of LDR as a potentially relevant indicator between banks' business models, their efficiency and the broader economic environment.

The second research question focused on the existence of nonlinear patterns and behavioral regimes and their impact on profitability. ANFIS Model 1 (LDR, CIR, GDP, CPI → ROE) identified pronounced profitability regimes, with very high ROE values occurring only under specific input combinations. In particular, very high LDR combined with medium CIR values results in very high ROE, whereas almost all other combinations of LDR and CIR yield medium or low ROE. At the same time, medium LDR values combined with very high CIR consistently generate very low ROE. These findings suggest that the potential benefits of more intensive lending and active utilization of the deposit base (high LDR) translate into profitability only when operational efficiency is maintained (CIR is not high), whereas operational inefficiency acts as a dominant „brake“ that can offset the positive effects of other variables. Furthermore, the results provide initial evidence that for very high ROE, a „more stable“ macro regime (e.g., medium GDP and CPI) is more favorable than cyclical extremes, whereas very low ROE appears under certain combinations of extreme LDR values with very high GDP, as well as in weaker macroeconomic conditions (low GDP and low CPI). This pattern supports the conclusion that the LDR–ROE relationship is nonlinear and depends on the context of macroeconomic conditions and operational efficiency, consistent with the document’s argument on the trade-off between growth and risk/resilience in interpreting LDR.

The third research question examined how the macroeconomic environment modifies the relationship between LDR and CIR and their indirect effect on system performance. ANFIS Model 2 (LDR, GDP, CPI → CIR) showed that CIR is shaped through the interactions of LDR with GDP and CPI, and that extreme CIR values are more likely to occur under extreme macro regimes. Very high CIR appears particularly in the combination of very high LDR and very high GDP, suggesting that during periods of strong economic growth, coupled with more aggressive lending activity, cost pressures relative to revenues may increase. Furthermore, the combinations of GDP and CPI indicate that high CIR also occurs when both GDP and CPI are very low, as well as when both are very high, whereas very low CIR values tend to occur under “more stable” inflation conditions (medium CPI) across different growth phases. This implies that the macro environment does not only affect profitability directly, but also alters the conditions under which credit activity (LDR) translates into operational efficiency (CIR), and subsequently, indirectly, into profitability (ROE).

Overall, the findings suggest that the LDR can serve as a useful common indicator linking the funding structure, efficiency, and macroeconomic conditions

within the Croatian banking system. However, these findings should be interpreted with caution due to several inherent limitations. First, the analyzed period, although methodologically in line with EBA/SREP standards, provides a limited number of observations (n=37), which may affect the long-term stability of the identified fuzzy rules. Second, the use of aggregated data for the Croatian banking system may mask significant heterogeneity across individual credit institutions. Finally, the exclusion of variables such as net interest margins, non-performing loan (NPL) ratios and specific Basel III metrics (LCR/NSFR) means that the identified transmission mechanisms remain indicative rather than definitive.

This study contributes to the literature by treating LDR as a nonlinear mechanism, and not just as a mere liquidity indicator. The application of the ANFIS model has shown that profitability and efficiency are regime-dependent, thus complementing the adequacy of linear models in banking. The findings may be particularly relevant for economies characterised by structural liquidity surpluses and bank-dominated financial systems. Future research should: extend the analysis to the panel level of individual banks to test for heterogeneity, include additional variables (liquidity resilience, interest rate spreads and credit risk), analyze sub-periods of specific shocks and inflation regimes, decompose the LDR to model separately the dynamics of loans (L) and the deposit base (D).

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Acknowledgement of AI or AI-assisted tools use: ANFIS (Adaptive Neuro-Fuzzy Inference System) is a form of artificial intelligence (AI)**.** It is considered a hybrid, intelligent system that combines the learning capability of Artificial Neural Networks (ANN) with the reasoning capabilities of Fuzzy Logic (FL) to map input-output data pairs. When translating into English, the translator, who also proofread the manuscript, used the ChatGPT tool in some segments of the work.

REFERENCES

Athanasoglou, P. P., Brissimis, S. N., & Delis, M. D. (2008). Bank-specific, industry-specific and macroeconomic determinants of bank profitability. *Journal of International Financial Markets, Institutions & Money*, *18*(2), 121–136. https://doi.org/10.1016/j.intfin.2006.07.001

Basel Committee on Banking Supervision (2013). Basel III: The Liquidity Coverage Ratio and liquidity risk monitoring tools. Bank for International Settlements. Retrieved from: https://www.pfandbrief.de/wp-content/uploads/2024/11/ 20130106_bcbs_238_LCR_en.pdf? utm

Basel Committee on Banking Supervision-BCBS (2019). Basel III: Finalising post-crisis reforms. Bank for International Settlements. Retrieved from: https://www.bis.org/bcbs/publ/d424.htm?utm

Basel Committee on Banking Supervision- BCBS (2014). Basel III: The Net Stable Funding Ratio. Bank for International Settlements. Retrieved from: https://www.bis.org/bcbs/publ/d295.htm?utm

BIS (2010). Funding patterns and liquidity indicators before and after the crisis. *CGFS Publications.* Retrieved from: https://www.bis.org/publ/cgfs39.pdf?utm

Beck, T., Degryse, H., & Kneer, C. (2018). Is more finance better? Disentangling intermediation and size effects of financial systems. *Journal of Financial Stability*, *38*, 64–77.Retrieved from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id =2116106

Benazić, M., & Učkar, D. (2024). The impact of selected macroeconomic variables on house prices in Croatia, *Ekonomska misao i praksa*, *33*(1), 163-186. https://doi.org/10.17818/EMIP/2024/1.4

Berger, A. N., & Bouwman, C. (2009). Bank liquidity creation. Review of Financial Studies, *22* (9), 3779–3837. Retrieved from: https://academic.oup.com/rfs/article-abstract/22/9/3779/1571440?redirectedFrom=fulltext&login=false&utm; https://doi.org/10.1093/rfs/hhn104

Berger, A. N., & Bouwman, C. H. (2013). How does capital affect bank performance during financial crises? *Journal of Financial Economics*, *109*(1), 146–176. Retrieved from:https://www.sciencedirect.com/science/article/abs/pii/S0304405X13000512?utm; https://doi.org/10.1016/j.jfineco.2013.02.008

Bonner, C., & Eijffinger, S. (2015). *The impact of liquidity regulation on bank lending. Journal of Financial Intermediation*, *24*(3), 312–328. https://doi.org/10.1093/rof/rfv058

Borio, C., & Lowe, P. (2002). Asset prices, financial and monetary stability: Exploring the nexus. *BIS Working Paper* No. 114. Retrieved from: https://www.bis.org/publ/work114.pdf; https://doi.org/10.2139/ssrn.846305

Brlečić Valčić, S., Peša, A., & Čičin-Šain, D. (2025). Financial Swing for Well-Being: Jazz Economy and Modelling the Social Return of Sustainable Capital Markets. *Journal of risk and financial management*, *18*(10). 568-19. 10.3390/jrfm18100568; https://doi.org/10.3390/jrfm18100568

Brunnermeier, M., & Oehmke, M. (2013). *The maturity rat race. Journal of Finance*, *68*(2), 483–521. https://doi.org/10.1111/jofi.12005

Cornett, M., McNutt, J., Strahan, P., & Tehranian, H. (2011). *Liquidity risk management and credit supply in the financial crisis. Journal of Financial Economics*, *101*(2), 297–312. https://doi.org/ 10.1016/j.jfineco.2011.03.001

Demirgüç-Kunt, A., & Huizinga, H**.** (2010). Bank activity and funding strategies: The impact on risk and returns. *Journal of Financial Economics, 98*(3), 626–650. https://doi.org/10.1016/j.jfineco.2010.06.004

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, *91*(3), 401–419. Retrieved from: https://karlshell.com/wp-content/uploads/2015/09/diamondanddybvig.pdf; https://doi.org/10.1086/261155

Derviz, A., & Podpiera, J. (2010). *Funding costs and loan pricing by multinational bank affiliates. Journal of Financial Stability*, *6*(4), 145–155. Retrieved from: https://library.utia.cas.cz/separaty/2010/E/derviz-funding%20costs%20and%20loan%20pricing%20by%20multinational-bank-affiliates.pdf

Dietrich, A., & Wanzenried, G. (2011). *Determinants of bank profitability before and during the crisis: Evidence from Switzerland. Journal of International Financial Markets, Institutions & Money*, *21*(3), 307–327. https://doi.org/ 10.1016/j.intfin.2010.11.002

Dinger, V. (2009). Do foreign-owned banks affect banking system liquidity? *Journal of Comparative Economics*, *37*(4), 647–657. https://doi.org/10.1016/j.jce.2009.04.003

Disyatat, P. (2011). The bank lending channel revisited. *Journal of Monetary Economics*, *58*(1), 1–12. https://doi.org/10.1111/j.1538-4616.2011.00394.x

European Banking Authority-EBA. (2020). *Risk Dashboard.* Retrieved from:https://www.esma.europa.eu/sites/default/files/library/esma50-165-1371_risk_dashboard_no_2_2020.pdf

European Banking Authority-EBA. (2021). *Risk Dashboard.* Retrieved from: https://data.europa. eu/data/ datasets/eba-risk-dashboard-2021?locale=en

European Banking Authority-EBA. (2022). *Risk Assessment of the European Banking System. EBA Report*. Retrieved from: https://www.eba.europa.eu/sites/default/files/document_library/Risk%20Analysis%20and%20Data/Risk%20Assessment%20Reports/2022/RAR/1045298/Risk%20Assessment%20Report%20December%202022.pdf

European Banking Authority-EBA. (2023). *Risk Dashboard – Data as of Q4 2023. EBA Publication*. Retrieved from:https://www.eba.europa.eu/risk-and-data-analysis/risk-analysis/risk-monitoring/risk-dashboard

European Banking Authority-EBA. (2024). *Risk Dashboard*. *EBA*. Retrieved from: ttps://www.eba.europa.eu/publications-and-media/publications/risk-assessment-report-july-2024

European Banking Authority-EBA. (2025). *Risk Dashboard Q1 2025*. Retrieved from: https://www.eba.europa.eu/sites/default/files/2025-08/1d0da81e-a9ec-4ee6-acf0-6bd1dcd2fd20/EBA%20Dashboard%20-%20Q12025.pdf

European Central Bank-ECB. (2016). *Report on financial structures*. Retrieved from: https://www.ecb.europa.eu/press/pr/date/2016/html/pr161027.en.html

European Central Bank-ECB. (2020). *Financial Stability Review*. Retrieved from: https://www.ecb.europa.eu/pub/ financial_stability/fsr/html/ecb.fsr202011~b7be9ae1f1.en.html

European Central Bank-ECB. (2023). *Financial Stability Review*. Retrieved from:https://www.ecb.europa.eu/pub/pdf/fsr/ecb.fsr202305~65f8cb74d7.en.pdf

European Central Bank-ECB. (2024). *Supervisory Banking Statistics*. Retrieved from: https://www.bankingsupervision.europa.eu/framework/statistics/html/index.en.html

European Central Bank-ECB. (2025). *Financial Stability Review*. Retrieved from: https://www.ecb.europa.eu/press/financial-stability-publications/fsr/html/index.en.html

European Securities and Markets Authority -ESMA. (2023). TRV – Trends, Risks and Vulnerabilities Report. Retrieved from: https://www.esma.europa.eu/document/esma-report-trends-risks-and-vulnerabilities-no-2-2023

European Securities and Markets Authority -ESMA. (2021). *Risk Dashboard.* Retrieved from: https://www.esma.europa.eu/sites/default/files/esma50-165-1761_risk_dashboard_no_1_2021.pdf

Everitt, B. S., Landau, S., Leese, M., & Stahl, D. (2011). *Cluster analysis* (5th ed.). John Wiley & Sons. Wiley Online Library; https://doi.org/10.1002/9780470977811

Federal Reserve System-FED. (2017). *Supervision and Regulation Report.* Retrieved from: https://www.federalreserve.gov/publications/2017-ar-supervision-and-regulation.htm

Federal Reserve System-FED. (2023). *Supervision and Regulation Report*. Washington, D.C. Retrieved from: https://www.federalreserve.gov/publications/files/202311-supervision-and-regulation-report.pdf

Federal Reserve System-FED. (2024). *Financial Stability Report*. Washington, D.C. Retrieved from: https://www.federalreserve.gov/publications/files/financial-stability-report-20241122.pdf

Heider, F., & Hoerova, M. (2018). Liquidity hoarding and interbank market spreads. *Journal of Financial Economics*, *128*(3), 564–584. https://doi.org/10.1016/j.jfineco.2015.07.002

Iannotta, G., Nocera, G., & Sironi, A. (2007). Ownership structure, risk and performance in the European banking industry. *Journal of Banking & Finance*, *31*(7), 2127–2149. https://doi.org/10.1016/j.jbankfin.2006.07.013

Jain, A. K., & Dubes, R. C. (1988). *Algorithms for clustering data*. Prentice Hall. ACM Digital Library

Jang, J. S. R. (1993). ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Transactions on Systems, Man, and Cybernetics, 23*(3), 665–685. https://doi.org/10.1109/21.256541

Jorda, Ò., Schularick, M., & Taylor, A. (2016). Macrofinancial history and the new business cycle facts. *NBER Macroeconomics Annual*. https://doi.org/10.1086/690241

Kaufman, L., & Rousseeuw, P. J. (1990). *Finding groups in data: An introduction to cluster analysis*. John Wiley & Sons. Wiley Online Library; https://doi.org/10.1002/9780470316801

Lane, P. R., & McQuade, P. (2014). Domestic credit growth and international capital flows. *Scandinavian Journal of Economics*, *116*(1), 218–252. Retrieved from: https://econpapers.repec.org/RePEc:bla:scandj:v:116:y:2014:i:1:p:218-252.htm; https://doi.org/10.1111/sjoe.12038

Levaj, M., & Viljevac, M. (2025). Monetarna kontrakcija i porast kamatnih stopa u hrvatskom gospodarstvu – je li rast kamatnih stopa u Hrvatskoj doprinio rušenju inflacije? *Ekonomska misao i praksa*, *34*(1). https://doi.org/10.17818/EMIP/2025/25

Merler, S., & Pisani-Ferry, J. (2012). Sudden stops in the euro area. *Bruegel Policy Contribution*. Retrieved from: https://www.bruegel.org/system/files/wp_attachments/pc_2012_06.pdf; https://doi.org/10.5202/rei.v3i3.97

Mirzaei, A., & Moore, T. (2021). Bank funding structure, lending behaviour, and performance. *Journal of Banking & Finance, 127*, 106114. Retrieved from: https://www.sciencedirect.com/journal/journal-of-banking-and-finance/vol/127/suppl/C

Nguyen, M., & Boateng, A. (2013). Modeling liquidity behavior of banks using panel data. *International Review of Financial Analysis*, *29*, 141–151. Retrieved from: https://www.sciencedirect.com/journal/international-review-of-financial-analysis/vol/29/suppl/C

Ozili, P. K. (2019). Bank Loan-to-Deposit ratio and bank performance in Europe. *International Journal of Finance & Economics, 24*(1), 99–106. Retrieved from: https://onlinelibrary.wiley.com/journal/10991138

Pagano, M., & Langfield, S. (2014). Bank bias in Europe. ECB *Working Paper Series.* Retrieved from: https://www.econstor.eu/bitstream/10419/154230/1/ecbwp1797.pdf?utm

Pasiouras, F., & Kosmidou, K. (2007). Factors influencing the profitability of domestic and foreign commercial banks in the EU. *Research in International Business and Finance*, *21*(2), 222–237. https://doi.org/10.1016/j.ribaf.2006.03.007

Radovanov, A., Dragosavac, M., & Marcikić, A. (2023). Determinants of bank profitability: An international panel study. *MDPI Sustainability*, *15*(2), 995. Retrieved from:https://www.mdpi.com/ 2227-7390/11/19/4072

Takagi, T., & Sugeno, M. (1985). Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on Systems, Man, and Cybernetics, 15*(1), 116–132. https://doi.org/10.1109/TSMC.1985.6313399

The Math Works, Inc. (n.d.). *linkage — Agglomerative hierarchical cluster tree* [Documentation]. Retrieved January 6, 2026, from https://www.mathworks.com/help/stats/linkage.html MathWorks

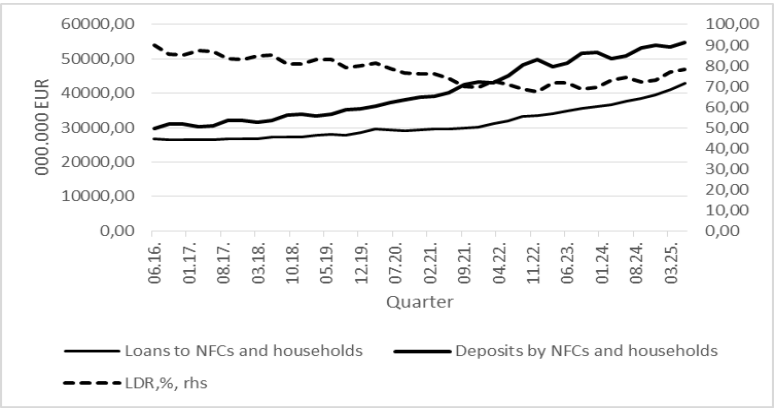
The Math Works, Inc. (n.d.). *Neuro-adaptive learning and ANFIS* [Documentation]. Retrieved January 6, 2026, from https://www.mathworks.com/help/fuzzy/neuro-adaptive-learning-and-anfis.html MathWorks

Tran, L. (2020). Bank-specific risks and profitability: A dynamic panel study. *International Review of Financial Analysis*, *67*, 101–132.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*(3), 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X

APPENDIX

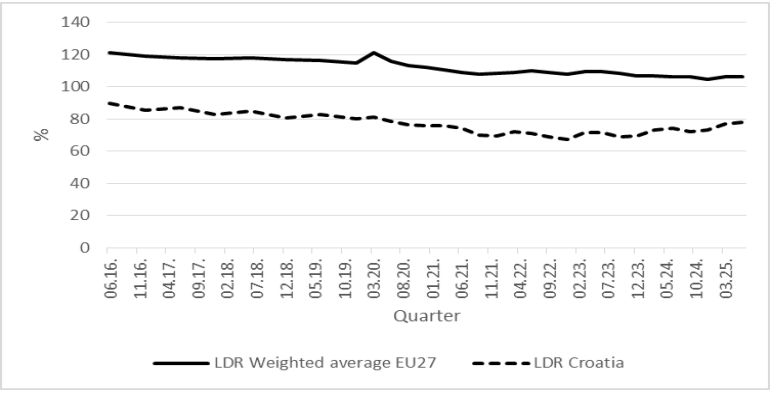
Figure 6 Bank loans and deposits with LDR levels



Note: Presented according to the methodology of EBA- Risk Dashboard, Risk Indicators' heatmap (Q1/2025). In total bank loans, the largest part is loans to non-financial companies (NFCs) and households (Q2/2025: 88%). Deposits of NFCs and households in total deposits make up over 93% of all deposits (Q2/2025).

Source: CNB statistics, author's calculations

Figure 7 Croatian LDR and EU27 average



Source: CNB statistics; www.eba.europa.eu; Risk Dashboard, 2025

Table 2 Variables for analysis

Quarters	Indicators, %				
	1	2	3	4	5
	LDR	ROE	CIR	GDP	CPI
06.16.	89,9	11,1	47,5	3,0	-1,6
09.16.	85,8	10,2	51,7	2,2	-0,9
12.16.	85,3	9,2	51,4	4,6	0,2
03.17.	87,3	3,1	53,6	2,3	1,1
06.17.	87,1	3,6	51,1	3,2	0,7
09.17.	83,5	5,2	49,6	4,4	1,4
12.17.	83,1	5,9	49,0	2,9	1,2
03.18.	84,6	9,7	51,4	1,9	1,1
06.18.	85,0	10,0	48,7	3,8	2,4
09.18.	81,0	9,8	48,4	3,0	1,4
12.18.	80,8	8,4	48,1	2,8	0,8
03.19.	83,2	9,5	47,7	4,8	0,9
06.19.	83,1	11,2	47,1	3,1	0,6
09.19.	79,3	10,4	46,3	2,9	0,8
12.19.	80,0	9,8	46,3	1,9	1,4
03.20.	81,2	7,1	53,1	-1,3	0,6
06.20.	78,5	5,6	54,8	-15,7	-0,2
09.20.	76,7	5,5	54,6	-11,0	0,0
12.20.	76,0	4,4	55,0	-3,7	-0,7
03.21.	76,1	6,8	53,3	3,8	1,2
06.21.	74,1	8,1	51,2	19,7	2,0
09.21.	70,1	8,3	50,4	15,9	3,3
12.21.	69,6	8,8	48,7	10,7	5,5
03.22.	72,4	9,5	53,6	7,8	7,3
06.22.	70,9	9,5	53,3	9,8	12,1
09.22.	68,8	10,2	51,8	7,9	12,8
12.22.	67,3	8,2	52,5	3,7	13,1
03.23.	71,5	14,0	46,8	2,4	10,7
06.23.	71,6	16,8	41,9	4,2	7,6
09.23.	68,9	16,9	40,0	2,4	6,7
12.23.	69,8	15,5	41,0	6,2	4,5
03.24.	73,2	18,1	39,1	3,7	4,1
06.24.	74,4	18,2	39,5	3,8	2,4
09.24.	72,3	17,6	39,1	4,0	1,6
12.24.	73,2	16,4	39,9	3,8	3,4
03.25.	77,1	15,4	41,2	3,3	3,2
06.25.	78,0	16,7	40,7	3,6	3,7

Source: Prepared by the authors based on CNB data

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OMJER KREDITA I DEPOZITA BANAKA U INTERAKCIJI S POKAZATELJIMA POSLOVANJA I MAKROEKONOMSKIM POKAZATELJIMA - DOKAZI IZ HRVATSKE

Sažetak

Ovaj rad analizira omjer kredita i depozita (LDR) u hrvatskom bankovnom sustavu u razdoblju 2016.–2025. te njegov odnos s operativnom učinkovitošću (CIR), profitabilnošću (ROE) i makroekonomskim pokazateljima (BDP, CPI). LDR se promatra kao nelinearan i kontekstualno uvjetovan mehanizam koji povezuje strukturu financiranja, učinkovitost i profitabilnost banaka. Primjenom hijerarhijskog grupiranja i adaptivnog neuro-fuzzy inferencijskog sustava (ANFIS) utvrđene su strukturne povezanosti među promatranim varijablama. Rezultati pokazuju da se visoka profitabilnost ostvaruje samo pri određenim kombinacijama LDR-a, CIR-a i stabilnih makroekonomskih uvjeta, dok izražena inflacija i ubrzan gospodarski rast negativno utječu na učinkovitost i ROE. Visok CIR pritom se pokazuje ključnim ograničavajućim čimbenikom. Istraživanje potvrđuje važnost konteksta u razumijevanju odnosa između bankarske aktivnosti, učinkovitosti i profitabilnosti.

Ključne riječi: banke, omjer kredita i depozita, bankovni i makroekonomski pokazatelji, ANFIS.

JEL klasifikacija: G21, C45, E44.