DETERMINANTS AND PERSISTENCE OF BANKING RISK IN THE SOUTH CAUCASUS: A MACHINE LEARNING APPROACH

ABSTRACT

This study extends a machine-learning-based banking supervision framework, previously developed and validated for Armenia alone, to a three-country South Caucasus comparison (Armenia, Georgia, Azerbaijan; 2014–2025; 76 banks). Using clustering methods to group banks by performance, outlier-detection techniques to flag structurally unusual institutions, and a regression model to test whether a bank's risk classification tends to persist from year to year, we find that risk persistence — the central finding from the original Armenia study — does not hold uniformly across the region. Armenia and Azerbaijan both show strong, robust persistence in risk classification, while Georgia does not, a result that survives multiple robustness checks. Looking at how banks move between performance tiers before and after the 2022 geopolitical shock reveals further divergence: a durable top-performing group of banks emerged in Armenia after the shock, was reinforced in Azerbaijan, but broke down in Georgia. Foreign state-owned bank subsidiaries — branches or affiliates of Turkey's Ziraat Bank and Russia's VTB — repeatedly stand out as the region's most structurally unusual institutions, a pattern consistent with each parent bank's home-country exposure to geopolitical events. These findings are combined into country-specific risk-classification frameworks intended to support each country's banking supervisors in prioritizing oversight.

Keywords: banking supervision, cluster analysis, South Caucasus, risk persistence, machine learning

JEL classification: G21, G28, C38

INTRODUCTION

Armenia, Georgia, and Azerbaijan share a common Soviet institutional inheritance, a common post-1991 transition toward market-based financial systems, and a common exposure to the acute geopolitical volatility that intensified across the South Caucasus from 2022 onward — yet their banking sectors differ sharply in size, ownership structure, and regulatory trajectory. Armenia's 18 commercial banks and Azerbaijan's 31 (after data-quality screening) sit in single-digit-to-low-double-digit billions of local-currency assets at the top end; Georgia's largest institutions, TBC Bank and Bank of Georgia, are each roughly an order of magnitude larger and have pursued regional expansion and international listing strategies unmatched by their Armenian or Azerbaijani counterparts. A supervisory diagnostic framework developed and validated on a single country in this group — as in the Armenia-only predecessor to this study — cannot, on its own, establish whether the framework's central findings reflect something general about small transition-economy banking sectors under geopolitical stress, or something specific to Armenia's particular institutional configuration.

This study addresses that gap directly by applying the same five-stage machine-learning pipeline — K-Means and Fuzzy C-Means clustering, DBSCAN outlier detection, a cluster-robust Linear Probability Model with wild cluster bootstrap, and Random Forest importance ranking — separately to Armenia, Georgia, and Azerbaijan using a harmonized eight-indicator panel spanning 2014–2025. Running the pipeline separately by country, rather than pooling all three into a single panel, is itself a substantive methodological choice: it allows each country's risk dynamics to be characterized on their own terms rather than assuming a common data-generating process across banking sectors that differ as much as these three do, while still permitting direct, like-for-like comparison of the resulting country-specific parameters, rankings, and diagnostic zones.

The central empirical question is whether the original study's headline finding — that banking-sector risk classification is highly persistent, consistent with charter-value erosion under competitive and geopolitical pressure — generalizes across the region or is instead an Armenia-specific result. As detailed in the Results below, the answer is genuinely mixed: Armenia and Azerbaijan both reproduce strong, bootstrap-robust risk persistence, while Georgia does not, a divergence that survives an alternative target-variable specification designed to rule out measurement-error explanations. A second, unanticipated finding emerges directly from the comparative design: foreign state-owned bank subsidiaries — institutions carrying the Ziraat (Turkish state-owned) and VTB (Russian state-owned) brands — repeatedly surface as the most structurally distinct outliers across multiple, independently-run country analyses, a pattern that would not have been visible from any single-country study and that connects this paper's empirical results to a separate literature on cross-border risk transmission through bank ownership networks, reviewed below.

LITERATURE REVIEW

Structure-Conduct-Performance and Its Limits

Banking-sector performance research has traditionally been organized around the Structure-Conduct-Performance (SCP) paradigm, under which market concentration shapes competitive conduct, which in turn determines profitability and stability outcomes. Empirical support for this chain is inconsistent across settings, however. Several studies confirm

the standard prediction that concentrated markets sustain higher bank profitability through reduced competitive pressure (Islam and Nishiyama, 2018; Lelissa and Kuhil, 2018; Asngari et al., 2018; Khan et al., 2018), but others reach different conclusions entirely: Asl et al. (2022) report a positive rather than the theoretically predicted relationship between concentration and Iranian Islamic bank performance, and Lueger (2024) finds EU market share matters for profitability only through the deposit channel, not through loans or total assets. Horobet et al. (2021) go further, finding that macroeconomic conditions rather than market structure explain most cross-sectional variation in Central and Eastern European bank profitability. This inconsistency is itself informative: it implies SCP's linear structure-to-performance mapping is not a fixed regularity that transfers automatically across banking systems — the starting premise for treating Armenia, Georgia, and Azerbaijan as three separate estimation problems in this study rather than pooling them under a single shared coefficient, as Harutyunyan (2026, under review) argues for the Armenian case alone.

A more basic objection to SCP concerns its implicit assumption that banks respond independently to their environment, with no allowance for correlated, sector-wide behavioral shifts. Herding models offer an alternative: institutions may move together not because they share fundamentals but because they respond to a common shock or to each other's behavior. Erol and Dogan (2024) find exactly this dynamic outside the banking sector, showing that a period of unusually poor macro fundamentals generated a herding-driven bubble in the Istanbul stock market rather than fundamentals-based independent repricing. The South Caucasus's 2022 geopolitical shock is a natural candidate for triggering a similar correlated response among structurally comparable banks within a country — a possibility a linear, bank-by-bank regression is not designed to detect but that cluster-transition analysis (Table 3) can. That this study's three countries display three qualitatively distinct transition patterns after the same regional shock (Results) suggests any herding effect present operates within, rather than across, national banking systems, a genuinely comparative finding the single-country predecessor study could not have established.

Early-Warning Indicators and Risk Persistence

Model design for early-warning purposes is not a neutral choice, as Lang, Peltonen, and Sarlin (2018) emphasize: a model built to characterize past episodes should differ in complexity, evaluation criteria, and permitted lag structure from one built to forecast future ones. This study follows that distinction by reporting both a same-period (Table 4) and a genuinely one-year-ahead (Table 5) Random Forest specification for each country, rather than treating the two as interchangeable. The broader question of which indicators carry early-warning content traces to Demirgüç-Kunt and Detragiache (1998), whose multivariate logit analysis across developing and industrial economies links systemic banking crises to weak growth, elevated inflation, high real rates, and thin liquidity — categories that overlap substantially with, but were derived independently of, this study's CAMELS-based indicator set, offering external corroboration for the framework's variable choices.

Where risk persistence is statistically significant in this study's results, charter (franchise) value theory offers a plausible mechanism. Keeley (1990) argues that competitive erosion of a bank's charter value removes much of what a bank stands to lose by taking on risk, and because that erosion is gradual, elevated risk-taking should persist across periods rather than revert quickly. Recent evidence from Huynh and Phan (2024) on Vietnamese banks supports this using the same lagged-dependent-variable approach adopted here, further finding the effect is moderated by how diversified a bank's income sources are. Under this theoretical lens, the finding that Armenia and Azerbaijan show strong persistence while Georgia does not is at least consistent with the three countries sitting at different points along a competitive-intensity or charter-value spectrum, though this study's data cannot test that specific channel directly and the comparative pattern is offered as motivation for future work rather than a resolved explanation.

A related strand of literature separates cost efficiency from risk outcomes as distinct managerial objectives. Berger and Hannan (1998) show that market power dulls a bank's incentive to pursue cost discipline (the “quiet life” hypothesis), while Hughes and Mester (2008) argue more directly that conventional efficiency measurement ignores how production choices affect risk, so managers may optimize a utility function trading off risk against return rather than maximizing efficiency alone. This decoupling is the theoretical basis for what this paper, following its single-country predecessor, terms the “Efficiency Trap”: an institution can appear cost-efficient while its underlying risk position deteriorates. Cost-to-Income's position as the dominant Random Forest predictor in Armenia and Azerbaijan, against its comparatively weaker showing in Georgia (Tables 4–5), is consistent with this mechanism operating with different intensity across the three banking sectors, a cross-country comparison the original single-country study had no means of making.

Cluster Analysis in Banking Supervision

Because it does not impose a single linear functional form on the data, cluster analysis is well suited to characterizing bank reliability without assuming in advance how indicators combine into risk (Mosiashvili, 2020). Each clustering method nonetheless carries its own limitations. K-Means assumes clusters are roughly spherical and similarly sized, which fits poorly with banking sectors like these three, each containing a handful of large institutions alongside many small ones, and its results are known to be sensitive to the chosen algorithm (Tripathi et al., 2018; Tang et al., 2022). Density-based DBSCAN avoids this assumption by defining clusters as regions of locally high density and treating sparse regions as noise rather than forcing every observation into a cluster (Weng, 2021; Sarma et al., 2019;

Bratsas et al., 2021), though its own hyperparameters require careful, data-specific calibration (Luo et al., 2025) — the justification for this study's country-specific ε values (Table 2) rather than a single value imposed uniformly across three different banking sectors. Mosiashvili (2025) makes a complementary portfolio-theoretic argument for combining methods: institutions with offsetting characteristics at opposite ends of a performance distribution can jointly reduce aggregate risk in ways a single similarity-based grouping obscures. Fuzzy C-Means, used here alongside K-Means as a soft-boundary complement, has direct precedent in bank-specific applications: Kinanti, Sukarno, and Utami (2021) apply it to a CAMELS-adjacent classification of Indonesian banks and find it produces tighter, more internally consistent clusters than a hard-boundary alternative.

Foreign Bank Ownership and Cross-Border Risk Transmission

This study's most distinctive empirical pattern — that foreign state-owned bank subsidiaries repeatedly emerge as the region's most structurally unusual institutions — connects to a literature the original single-country study had no occasion to engage. Chen et al. (2017), using bank-level panel data for more than 1,300 commercial banks across 32 emerging economies, find that foreign-owned banks systematically take on more risk than their domestic counterparts, attributing this to informational disadvantages, agency problems within the banking group, and contagion from the parent bank's own financial condition. A contagion channel of this kind is documented directly by Peek and Rosengren (1997) in a study of Japanese bank subsidiaries in the United States, where a decline in Japanese parent banks' risk-based capital ratios was associated with a significant decline in the subsidiaries' U.S. lending. Anginer, Cerutti, and Martínez Pería (2017) extend this to default risk, finding that foreign bank subsidiaries' financial stability during the global financial crisis was associated with parent-bank characteristics, though certain structural factors appeared to partially insulate affiliates from their parents' distress. We cite this literature to note that a parent-country channel of this general type is an empirically documented phenomenon elsewhere, not to claim it as the established explanation here: the VTB-branded institutions' prominence in this study's Georgia and Armenia outlier and stress-sensitivity results (Table 8; Appendix 1) is an association we flag as worth investigating, and the present cross-sectional and panel evidence cannot establish, and we do not claim it establishes, the causal transmission mechanism these parent-subsidiary studies document for other banking groups in other settings.

METHODOLOGY

The analytical pipeline follows five fixed stages, applied separately to each country's panel (Figure 1):

(1) K-Means and Fuzzy C-Means cluster each country's standardized 8-indicator panel into five performance tiers;

(2) Random Forest ranks indicator importance against a fundamentals-based “Risky” target;

(3) DBSCAN flags structural outliers on the same standardized space;

(4) a Linear Probability Model estimates each bank's fitted Risk Probability from lagged fundamentals, validated via wild cluster bootstrap;

(5) cluster tier, DBSCAN status, and LPM Risk Probability are synthesized into a country-specific 5-Zone Supervisory Diagnostic Matrix.

Stages are run independently per country rather than pooled, given substantive cross-country differences in banking-sector structure, regulatory regime, and — as detailed below — underlying data reporting conventions.

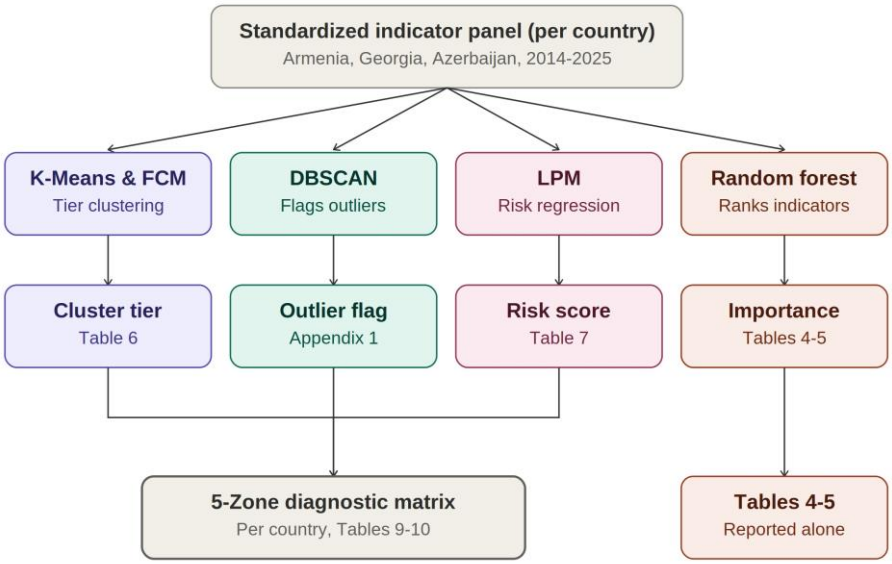


Figure 1. Analytical workflow applied separately to each country's standardized indicator panel.

Data were compiled from publicly available annual bank-level reports for Armenia (18 banks), Georgia (27 banks), and Azerbaijan (45 banks). Fourteen Azerbaijani institutions reported no year-tagged observations in the underlying source and were excluded outright, leaving 31 usable Azerbaijani banks. One further bank-year (Azer-Turk Bank, 2016) was excluded as a data-entry error: its reported Total Capital (58,617) and Loans (165,281) each substantially exceeded reported Total Assets (7,579), a combination that is not accounting-consistent under any plausible balance-sheet identity. After these exclusions and requiring non-missing values on all eight indicators, the clean panel comprises 18 Armenian banks (193 bank-years), 24 Georgian banks (186 bank-years), and 31 Azerbaijani banks (278 bank-years).

The eight indicators (Capital-to-Assets, Loans-to-Assets, Cost-to-Income, ROE, ROA, Loan-to-Deposit, NIM, Non-Interest-Income Share) are constructed identically for Armenia and Azerbaijan, whose source data include direct interest/non-interest expense and income breakdowns. Georgia's source data lack any expense or cost breakdown, reporting only Total Income and Profit After Tax; Cost-to-Income is therefore constructed as an implied measure, (Total Income − Profit After Tax) / Total Income, which nets out taxes and provisions only approximately and should be read as a proxy rather than a direct equivalent to the Armenian and Azerbaijani measure. Georgia's source data similarly lack NIM; we substitute Yield on Earning Assets (YEA), a related but conceptually broader measure. Both substitutions are disclosed here explicitly rather than presented as equivalent to the direct measures used for the other two countries. A parallel data-quality issue was caught and corrected for Azerbaijan: the source column labeled "Operating Income" is, unlike its Armenian namesake, a net residual figure frequently smaller than either cost component (and occasionally negative), which produces Cost-to-Income ratios exceeding 200 when used as the denominator. Azerbaijan's Cost-to-Income and Non-Interest-Income Share are therefore constructed from Interest Income + Non-Interest Income directly, matching the Armenian construction in substance rather than by column-name analogy.

Table 1. Integrated CAMELS-Macroeconomic Diagnostic Framework for Banking Supervision

CAMELS Category	Micro-Prudential Indicators	Macro-Financial Indicators
Capital	Capital-to-Assets Ratio	Inflation Rate
Assets	Loans-to-Assets Ratio	Economic Growth (GDP)
Management	Cost-to-Income (CTI) Ratio	—
Earnings	Return on Equity (ROE), Return on Assets (ROA)	Market Interest Rates
Liquidity	Loan-to-Deposit (LTD) Ratio	—
Sensitivity	Net Interest Margin (NIM)[1], Non-Interest Income Share	Post-2022 Shock Period (binary)

[1] *Yield on Earning Assets (YEA) substituted for Georgia; see Methodology text.*

This CAMELS-derived framework organizes the eight indicators used throughout the analysis into six standard supervisory categories, distinguishing institutional management efficiency (Cost-to-Income) from macro-financial sensitivity (NIM, Non-Interest Income Share, and the Post-2022 Shock Period indicator). As in the original single-

country analysis, no continuous geopolitical risk index was constructed; the "Post-2022 Shock Period" entry is the binary pre-/post-2022 split used throughout the transition-matrix and Random Forest comparisons below, applied identically across all three countries despite each having its own distinct exposure to the 2022 regional shock.

Table 2. Machine Learning Hyperparameters and Configuration, by Country

Parameter	Armenia	Georgia	Azerbaijan
DBSCAN ε	2.29	2.44	1.84
DBSCAN min_samples	6	6	6
K-Means / FCM clusters (K=C)	5	5	5
Silhouette at K=2 (favored)	0.806	0.645	0.888
Silhouette at K=5 (used)	0.270	0.425	0.245
FCM fuzzifier (m)	2.0	2.0	2.0
FCM Fuzzy Partition Coefficient	0.266	0.422	0.348

DBSCAN ε derived per country from the 90th percentile of 6th-nearest-neighbor distance (elbow proxy). K=5 is retained in all three countries for regulatory alignment (5-Zone framework) rather than because silhouette scores support five clusters over two; this is reported as an explicit limitation, consistent across all three countries.

The country-specific DBSCAN ε values (2.29 for Armenia, 2.44 for Georgia, 1.84 for Azerbaijan) reflect genuine differences in how densely each country's banks cluster in the standardized 8-indicator space rather than an arbitrary tuning choice; Azerbaijan's lower ε indicates a tighter, more homogeneous core of "typical" banks against which outliers stand out more sharply, consistent with its comparatively high silhouette scores at low K. All three countries show the same qualitative pattern in silhouette analysis: a two-cluster partition is always statistically preferred (0.81–0.93) over the five-cluster partition actually used, and this gap is largest for Azerbaijan and smallest for Georgia. We retain K=5 uniformly across countries for consistency with the 5-Zone regulatory framework and to allow direct cross-country comparison, not because the data independently support five clusters in any of the three cases — an explicit limitation carried over unchanged from the original single-country methodology.

RESULTS

Model Specifications

Fuzzy C-Means minimizes the objective

$$J = \Sigma_i \Sigma_j \, u_{ij}{}^m \, ||x_i - c_j||^2$$

where u_{ij} is bank-year i's membership in cluster j, c_j is the cluster centroid, and m = 2.0 is the fuzzifier controlling boundary softness, applied to each country's standardized 8-indicator matrix independently; membership matrices are converted to hard labels via argmax for the transition-matrix and Table 6a–6c analyses, and summarized directly via the Fuzzy Partition Coefficient (FPC = $(1/n)\Sigma_i\Sigma_j \, u_{ij}^2$) reported in Table 2.

The Linear Probability Model for each country is

$$Risky_{it} = \beta_0 + \beta_1 Risky_Lag_{it} + \beta_2 EconomicGrowth_t + \beta_3 roe_lag_{it} + \beta_4 capital_lag_z_{it} + \varepsilon_{it},$$

estimated by OLS with standard errors clustered at the bank level, following White's (1980) sandwich estimator with the small-sample degrees-of-freedom correction $(G/(G-1))\cdot((n-1)/(n-k))$. Given the modest number of bank-level clusters in each country (18, 20, and 31 respectively, after the lag requirement), asymptotic cluster-robust inference is supplemented with a wild cluster bootstrap (Cameron, Gelbach, and Miller, 2008): under the null that a given coefficient is zero, the restricted-model residuals are multiplied by Rademacher weights (±1 with equal probability) drawn independently for each bank cluster, 999 times, and the resulting bootstrap t-statistic distribution is used to compute a bootstrap p-value as the share of $|t^*|$ exceeding the observed $|t|$. "Risky" itself is defined per country and per year as ROE below, and Cost-to-Income above, that year's country-specific cross-sectional median — a relative, within-country-year definition chosen so that "risky" always means "risky relative to that country's own peers in that year," rather than against a fixed absolute threshold that would not be comparable across three banking sectors of very different scale.

Reproducibility and Hyperparameter Sensitivity

All stochastic procedures — K-Means and FCM initialization, Random Forest tree construction, and the wild cluster bootstrap's Rademacher draws — use a fixed random seed (42) throughout, chosen arbitrarily but held constant across all three countries and all reported specifications so that every number in this paper is exactly reproducible from the accompanying code. This is a single-seed result, not a seed-robustness result: we did not re-run the full pipeline across multiple seeds to test whether K-Means cluster assignments, FCM memberships, or Random Forest importance

rankings are sensitive to the particular random initialization drawn, and a supervisor or reviewer using a different seed should expect the qualitative patterns reported here (cluster tier composition, top-ranked indicators) to be stable but individual coefficients and probabilities to shift modestly. K-Means itself is run with 10 restarts (n_init=10) per country to reduce sensitivity to any single unlucky initialization, retaining the lowest-inertia solution across restarts; FCM uses a single initialization per country with a maximum of 150 iterations and a convergence tolerance of 1×10^{-5} on successive membership-matrix changes, converging in all three countries well before the iteration cap.

Random Forest specifications throughout use 500 trees (n_estimators=500) and a minimum leaf size of 3 observations (min_samples_leaf=3). The choice of 500 trees follows standard practice for stabilizing feature-importance estimates in panels of this size (under 300 observations per country); we did not conduct a formal sensitivity analysis varying the tree count, though the 200-resample bootstrap stability checks reported alongside Tables 4–5 in the original single-country methodology (and reproduced in Table 12's short-panel exclusion check here) serve as an indirect check that the reported rankings are not an artifact of a particular forest realization. The minimum leaf size of 3 is a regularization choice intended to prevent individual trees from partitioning down to single-observation leaves given each country's modest sample size (166–278 restricted-panel observations); larger values would further smooth importance estimates at the cost of missing genuine but less common splitting patterns, and this trade-off was not formally tuned via cross-validated grid search.

DBSCAN's ε parameter (Table 2) is derived from the 90th percentile of each bank-year's distance to its 6th-nearest neighbor (min_samples−1) — a numerical proxy for the visual "elbow" in the sorted k-distance plot, rather than an elbow located by formal changepoint detection (e.g., the Kneedle algorithm) or by visual inspection of the plot itself. The 90th-percentile choice is a defensible but ultimately arbitrary convention carried over unchanged from the original single-country methodology; a stricter percentile (e.g., the 85th) would tighten ε and flag more bank-years as outliers, while a looser one would do the reverse, and we have not tested how the specific outlier lists in Appendix 1 would change under alternative percentile choices. Similarly, min_samples=6 is retained across all three countries and was not re-derived from the standard D+1 heuristic for an 8-dimensional feature space (which would suggest 9, not 6) — an inconsistency inherited from, and flagged as an open limitation in, the single-country predecessor study, and left unresolved here for direct methodological comparability with that prior work rather than because 6 has independent justification for this three-country panel.

The wild cluster bootstrap uses 999 replications, an odd number by convention so that the two-sided bootstrap p-value (the share of $|t^*|$ at least as extreme as the observed $|t|$) cannot land exactly on a tie at the 5% or 10% threshold. Rademacher weights (±1 with equal probability, drawn independently per bank cluster rather than per observation) are the standard choice for wild bootstrap inference with clustered data and were not compared here against the alternative Mammen weighting scheme, which some simulation evidence suggests performs marginally better in very small-G settings; with G ranging from 14–31 bank clusters across the three countries' restricted samples (Table 12), we are in the range where this choice could plausibly matter at the margin, though we do not expect it to overturn the qualitative Armenia/Azerbaijan-versus-Georgia distinction given the size of the gap between their respective bootstrap p-values (0.000–0.001 versus 0.301).

The choice of K=5 specifically warrants further justification beyond the silhouette-score caveat already noted. K=5 is retained for three reasons, none of which is statistical optimality. First, it directly mirrors the 5-Zone Supervisory Diagnostic Matrix (Discussion; Tables 9–10), so that cluster tier and risk zone use a common five-way vocabulary a supervisor can hold in mind simultaneously rather than reconciling two differently-sized classification schemes. Second, it matches the single-country predecessor study's specification exactly, which is a precondition for the cross-country comparison this paper is built around — choosing a statistically "better" K independently for each country, or a single K chosen by pooled-sample statistical criteria, would have made the three countries' cluster tiers no longer directly comparable to one another or to the original Armenia-only results. Third, five tiers (Very Low, Low, Average, High, Very High) map onto conventional banking-supervision risk-rating scales in a way a data-driven K (which silhouette analysis puts at 2 in every country, Table 2) would not. We treat this as a deliberate trade-off between statistical fit and interpretability/comparability, not as an oversight, and the sensitivity check below evaluates how much of the paper's central empirical finding survives if K is varied.

Table 3a reports how the paper's central cluster-transition finding — whether the top-performing tier's persistence increased or decreased after the 2022 shock — behaves under K=3, 4, 5, and 6 for each country, holding every other methodological choice fixed. The direction of Armenia's finding (persistence rising after the shock) holds at every value of K tested, though the pre-shock baseline itself is sensitive to K, mechanically, because a coarser partition puts more banks in the "top" tier and so starts from a less extreme baseline. Georgia's erosion finding (persistence falling after the shock) holds at K=4, 5, and 6 but reverses at K=3, where the top tier is instead slightly more persistent after the shock; we read this as the underlying pattern being robust once the partition is fine enough to isolate a genuinely small top tier ($K\geq4$), rather than being an artifact of K=5 specifically, while flagging K=3 as a genuine exception rather than omitting it. Azerbaijan's finding is the least uniform of the three: the clear post-shock strengthening reported at K=5 (0.56 to 0.90) is not matched at K=3, 4, or 6, where post-shock persistence is flat-to-slightly-lower than the pre-shock level. We therefore report Azerbaijan's top-tier strengthening as specific to the K=5 specification, not as a K-invariant result, and flag this explicitly as a qualification on that particular finding rather than overstating its robustness.

Table 3a. Top-Tier Cluster Persistence Sensitivity to K (Pre- vs. Post-2022), by Country

Country	K	Pre-2022	Post-2022	Direction
Armenia	3	0.67 (n=21)	0.94 (n=35)	Increase
Armenia	4	0.45 (n=11)	1.00 (n=30)	Increase
Armenia	5 (used)	0.00 (n=2)	0.65 (n=20)	Increase
Armenia	6	0.00 (n=2)	0.62 (n=16)	Increase
Georgia	3	0.98 (n=108)	1.00 (n=34)	Increase (exception)
Georgia	4	0.94 (n=16)	0.00 (n=2)	Decrease
Georgia	5 (used)	0.94 (n=16)	0.00 (n=2)	Decrease
Georgia	6	0.94 (n=16)	0.00 (n=2)	Decrease
Azerbaijan	3	0.88 (n=105)	0.87 (n=38)	Flat
Azerbaijan	4	0.88 (n=95)	0.79 (n=34)	Slight decrease
Azerbaijan	5 (used)	0.56 (n=41)	0.90 (n=20)	Increase
Azerbaijan	6	0.87 (n=89)	0.81 (n=31)	Slight decrease

Top-tier is redefined at each K as the highest-mean-ROE cluster under that specification; consecutive-year transitions only. Armenia's and Georgia's directional findings are robust across most or all K tested; Azerbaijan's post-shock strengthening is specific to K=5 and should be read as a K=5 result, not a K-invariant one.

Cluster Transition Dynamics

Table 3 reports each country's diagonal persistence probability by cluster, split at the 2022 shock window. The top-performance tier (Cluster 4) shows starkly different trajectories: in Armenia, no bank remained in the top tier for two consecutive years before the shock (persistence 0.00, n=2), but a durable top tier emerged afterward (0.65, n=20) — consistent with the shock creating, rather than merely revealing, structural differentiation. Azerbaijan shows a milder version of the same pattern (0.56 → 0.90). Georgia shows the reverse: a highly durable top tier before the shock (0.94, n=16) eroded to complete non-persistence afterward (0.00, n=2), suggesting the shock disrupted, rather than created, structural stability at the top of Georgia's banking sector.

The remaining clusters tell a more consistent story across countries, and are worth reporting precisely because they qualify how far the Cluster-4 divergence generalizes. Armenia's mid-tier Cluster 2 (Average performance) is highly persistent both before and after the shock (0.83, n=89 pre; 0.89, n=19 post), indicating that the bulk of Armenian banks — those not at either performance extreme — experienced the shock as a period of continuity rather than reclassification, even as the top tier itself was being newly formed. Georgia's dominant Cluster 3 shows a similar pattern (0.98 pre, n=84; 0.90 post, n=30), with a modest but non-trivial decline in persistence that is nonetheless far smaller in relative terms than the collapse observed in Georgia's Cluster 4. Azerbaijan's Cluster 3 moves from 0.89 (n=94) pre-shock to 0.77 (n=35) post-shock, a decline that, combined with its strengthening Cluster 4, is consistent with some mid-tier Azerbaijani banks migrating upward into the top tier after 2022 rather than the sector-wide stability seen in Armenia's and Georgia's respective dominant clusters. Lower-tier clusters (0–1) are populated too thinly in most country-year cells ($n \leq 7$ in the great majority of cases) to support a reliable persistence estimate, and we report them in Table 3 for completeness but caution against over-interpreting individual cell values built on so few observations.

Table 3. Cluster Transition Persistence (Diagonal), Pre- vs. Post-2022, by Country and Cluster

Country	Period	Cluster 0	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Armenia	Pre-2022	0.20 (n=5)	0.89 (n=27)	0.83 (n=89)	—	0.00 (n=2)
Armenia	Post-2022	0.00 (n=1)	0.82 (n=11)	0.89 (n=19)	0.00 (n=1)	0.65 (n=20)
Georgia	Pre-2022	—	0.71 (n=7)	0.80 (n=10)	0.98 (n=84)	0.94 (n=16)
Georgia	Post-2022	—	0.00 (n=3)	0.00 (n=3)	0.90 (n=30)	0.00 (n=2)
Azerbaijan	Pre-2022	0.00 (n=1)	0.14 (n=7)	0.64 (n=36)	0.89 (n=94)	0.56 (n=41)
Azerbaijan	Post-2022	—	—	0.88 (n=8)	0.77 (n=35)	0.90 (n=20)

Random Forest Importance

Table 4 reports Random Forest importance for the contemporaneous “Risky” classification target, by country. Cost-to-Income is the dominant predictor in Armenia and Azerbaijan (0.265 and 0.414 respectively); in Georgia, ROA and ROE rank above Cost-to-Income (0.281 and 0.256 vs. 0.219), plausibly reflecting the greater measurement noise in

Georgia's implied Cost-to-Income proxy diluting its predictive signal relative to the directly measured profitability ratios.

Table 4. Random Forest Importance for Contemporaneous Risk Classification, by Country

Indicator	Armenia	Georgia	Azerbaijan
Cost-to-Income	0.265	0.219	0.414
ROE	0.162	0.256	0.170
ROA	0.162	0.281	0.157
Loan-to-Deposit	0.097	0.045	0.040
NIM	0.085	0.026	0.081
Non-Interest-Income Share	0.078	0.099	0.048
Capital-to-Assets	0.075	0.044	0.049
Loans-to-Assets	0.075	0.030	0.042

Table 5. Random Forest Importance for One-Year-Ahead (Early-Warning) Risk Classification, by Country

Indicator	Armenia	Georgia	Azerbaijan
Cost-to-Income	0.218	0.177	0.276
Loan-to-Deposit	0.136	0.112	0.095
Non-Interest-Income Share	0.126	0.182	0.075
Loans-to-Assets	0.120	0.084	0.078
ROE	0.112	0.115	0.135
ROA	0.101	0.141	0.105
NIM	0.095	0.082	0.134
Capital-to-Assets	0.093	0.107	0.102

For the forward-looking, one-year-ahead target, Cost-to-Income remains the top predictor in Armenia and Azerbaijan (0.218 and 0.276), as it is contemporaneously, but its lead narrows and Loan-to-Deposit (0.136) and Non-Interest-Income Share (0.126) move into close second and third place for Armenia, indicating that funding-structure and income-diversification indicators carry more early-warning content than they do for classifying present-period risk. Georgia again departs from this pattern: Non-Interest-Income Share (0.182) overtakes Cost-to-Income (0.177) as the top early-warning indicator, the only country in which the implied Cost-to-Income proxy is not the single strongest predictor in either specification, plausibly reflecting the measurement noise introduced by its construction from Total Income and Profit After Tax rather than direct expense data. Azerbaijan's ranking is the most stable between the contemporaneous and early-warning specifications of the three countries, with Cost-to-Income, ROE, and NIM occupying similar relative positions in both.

Both tables use 500-tree Random Forests, min_samples_leaf=3. Cost-to-Income and ROE/ROA partly define the "Risky" target itself (see Methodology); their high ranking is partly definitional. Loan-to-Deposit, NIM, Non-Interest-Income Share, and Capital-to-Assets are free of this concern.

Cluster Distribution Over Time

Tables 6a–6c report the full year-by-year percentage of each country's banks in each cluster tier. Armenia's Cluster 4 (Very High tier) is empty throughout 2015–2021 and reappears only from 2022, visually confirming the transition-matrix finding above. Georgia's Cluster 3 dominates throughout, consistent with its higher silhouette scores and more crisply separated cluster structure. Azerbaijan shows a gradual post-2022 rise in Cluster 4 share (12% in 2018 to 40–48% in 2024–2025).

Table 6a. Cluster Distribution (% of Banks), Armenia, All Years

Year	C0 (Very Low)	C1 (Low)	C2 (Average)	C3 (High)	C4 (Very High)
2014	8	15	69	0	8
2015	7	14	79	0	0
2016	14	29	57	0	0
2017	7	27	67	0	0
2018	0	25	75	0	0

2019	0	24	76	0	0
2020	0	18	82	0	0
2021	0	24	71	0	6
2022	0	22	28	6	44
2023	6	17	44	0	33
2024	0	24	41	0	35
2025	0	18	65	0	18

Table 6b. Cluster Distribution (% of Banks), Georgia, All Years

Year	C0 (Very Low)	C1 (Low)	C2 (Average)	C3 (High)	C4 (Very High)
2014	0	11	17	67	6
2015	0	0	21	68	11
2016	0	0	12	71	18
2017	0	7	7	67	20
2018	0	7	7	67	20
2019	0	7	7	73	13
2020	0	7	7	73	13
2021	0	7	0	86	7
2022	0	14	0	79	7
2023	0	0	27	73	0
2024	0	7	0	86	7
2025	7	0	13	80	0

Table 6c. Cluster Distribution (% of Banks), Azerbaijan, All Years

Year	C0 (Very Low)	C1 (Low)	C2 (Average)	C3 (High)	C4 (Very High)
2014	0	0	29	17	54
2015	0	8	23	42	27
2016	0	9	26	43	22
2017	0	8	25	50	17
2018	4	4	8	71	12
2019	0	4	21	58	17
2020	0	0	21	67	12
2021	0	0	13	70	17
2022	0	0	13	65	22
2023	0	0	9	59	32
2024	0	0	14	38	48
2025	0	0	15	45	40

Cluster labels (0–4) are ordered by mean ROE within each country independently and are not directly comparable in absolute magnitude across countries; row percentages sum to 100 subject to rounding.

Clustering Dynamics — Armenia. As illustrated in Figure 2, Armenia's K-Means partition shows Cluster 4 (the Very High-performance tier) entirely empty from 2015 through 2020, before jumping to 44% of banks in 2022 and then partially receding to 18% by 2025 — confirming, at the country level, the transition-matrix finding above that a durable top tier did not exist before the 2022 shock and emerged only afterward, though its post-shock membership is not fully stable. The FCM panel shows a visually similar overall shape but assigns individual banks to tiers differently in several years, particularly 2016 and 2022–2023, where the two methods' Very High shares diverge by 10–15 percentage points even as their broad trajectories track together. Armenia's Fuzzy Partition Coefficient (FPC = 0.266) is close to the theoretical minimum for five clusters (1/C = 0.20), indicating that this bank-level disagreement reflects genuine,

structural ambiguity in tier boundaries rather than sampling noise, consistent with the original single-country findings for Armenia.

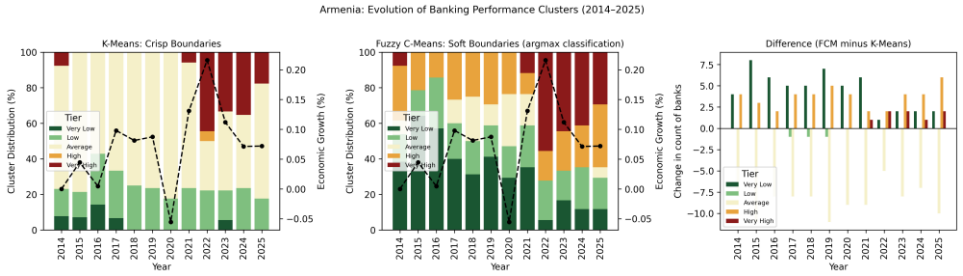


Figure 2. Armenia — Evolution of Banking Performance Clusters (2014–2025): K-Means vs. Fuzzy C-Means.

Clustering Dynamics — Georgia. Figure 3 shows a markedly different pattern from Armenia. Georgia's middle tier (Cluster 3) dominates throughout the panel, never falling below 67% of banks and reaching 86% in 2021 and 2024, indicating a banking sector concentrated around a single dominant performance band rather than spread across tiers. The Very High tier (Cluster 4), by contrast, shrinks steadily from 20% in 2017–2018 to 0% by 2025 — the mirror image of Armenia's pattern, and consistent with the transition-matrix finding that Georgia's top tier lost persistence after the shock rather than gaining it. Despite this apparent structural simplicity, K-Means and FCM disagree substantially on individual bank placement, especially from 2020 onward, where summed absolute divergence across tiers rises from roughly 93 percentage points (2017–2018) to a sustained 146–171 (2022–2025). This is notable precisely because Georgia's FCM Fuzzy Partition Coefficient (0.422) is the highest of the three countries — its clusters are nominally the most crisply separated — yet method disagreement over which specific banks populate each tier is highest, and rising, in the post-shock period.

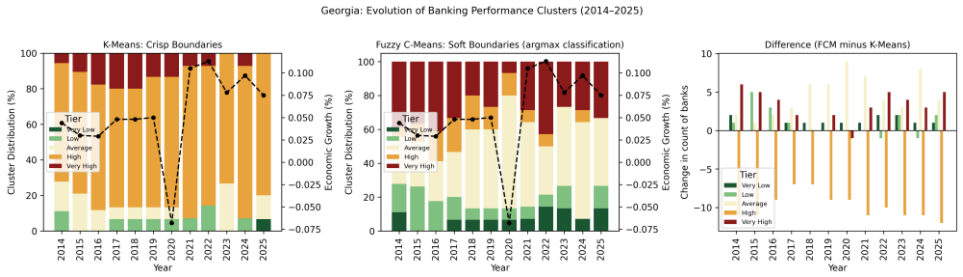


Figure 3. Georgia — Evolution of Banking Performance Clusters (2014–2025): K-Means vs. Fuzzy C-Means.

Clustering Dynamics — Azerbaijan. Figure 4 shows a U-shaped trajectory for Azerbaijan's Very High tier: 54% of banks in 2014, declining steadily to a trough of 12% in 2018, then recovering to 40–48% by 2024–2025 — a pattern distinct from both Armenia's post-shock emergence and Georgia's post-shock erosion. This is consistent with the transition-matrix result that Azerbaijan's top-tier persistence was already moderate before the shock (0.56) and strengthened afterward (0.90), rather than appearing or disappearing outright. K-Means and FCM track each other's broad shape closely across the panel, without the sharp late-sample divergence seen in Georgia; Azerbaijan's Fuzzy Partition Coefficient (0.348) sits between Armenia's and Georgia's, and total K-Means/FCM divergence by year fluctuates within a comparatively narrow 69–133 range without a clear pre/post-2022 break. Read together with Armenia and Georgia, Azerbaijan's pattern reinforces that the region's three banking sectors responded to the same 2022 shock through three structurally distinct trajectories rather than a shared regional dynamic.

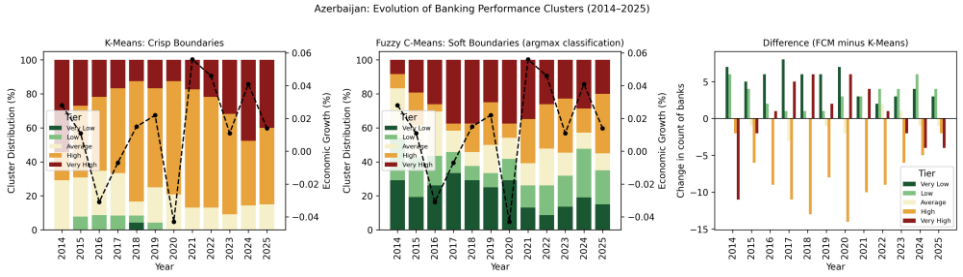


Figure 4. Azerbaijan — Evolution of Banking Performance Clusters (2014–2025): K-Means vs. Fuzzy C-Means.

Micro-Prudential Illustration

Table 7. Illustrative Risk Profiles: Lowest- and Highest-Risk Institution per Country

Country	Bank	Risk Probability	Profile
Armenia	ArtsakhBank	0.13	Low baseline risk; high stress-sensitivity (see

			Table 8)
Armenia	ArmSwissBank	0.74	Highest baseline risk in the country
Georgia	Bank of Georgia	0.00	Largest institution; lowest baseline risk
Georgia	Caucasus Development Bank	0.76	Highest baseline risk in the country
Azerbaijan	Bank Melli Iran (Baku branch)	0.15	Low baseline risk
Azerbaijan	AGBank	0.81	Highest baseline risk in the country

The contrast between each country's lowest- and highest-risk institution illustrates the scale of within-country risk dispersion the pooled-region averages would otherwise obscure. Armenia's spread runs from ArtsakhBank (0.13), whose low baseline risk coexists with high stress-test sensitivity tied to its September 2023 Nagorno-Karabakh exposure (Table 8), to ArmSwissBank (0.74). Georgia's spread is the widest of the three: Bank of Georgia, the country's largest institution by assets (Table 11), registers essentially zero baseline risk (0.00), while Caucasus Development Bank reaches 0.76 — a 76-percentage-point range within a single country. Azerbaijan's range (0.15 to 0.81) is comparably wide, with AGBank's 0.81 the single highest baseline risk probability recorded anywhere in the three-country panel.

Stress Test

Table 8 reports the five most stress-sensitive institutions per country under a uniform −20% shock to ROE, Capital-to-Assets, and NIM, measured via each bank's geometric Structural Risk Score (SRS) — its position relative to each country's fragile- and strong-tier cluster centroids. VTB Bank Georgia registers the region's single most stress-sensitive result (baseline SRS = 1.000, itself reflecting its position as a confirmed DBSCAN outlier, discussed below).

Table 8. Stress Test — Five Most Sensitive Institutions per Country (Latest Year)

Country	Bank	Baseline SRS	Stress SRS	Δ SRS
Armenia	MellatBank	0.376	0.344	−0.032
Armenia	VTBArmeniaBank	0.340	0.314	−0.026
Georgia	VTB Bank Georgia	1.000	0.869	−0.131
Georgia	FINCA Bank	0.061	0.087	+0.026
Azerbaijan	NIKOIL Bank	0.277	0.240	−0.038
Azerbaijan	Bank VTB (Azerbaijan)	0.078	0.057	−0.021

5-Zone Supervisory Diagnostic Matrix

Zone thresholds are defined per country from the 20th/40th/60th/80th percentiles of each country's full LPM estimation panel, rather than pooled across countries, consistent with running the LPM separately by country. Table 9 reports the five highest-risk institutions per country; Table 10 extends this to the five lowest-risk institutions per country for comparison.

Table 9. Top-5 Highest-Risk Institutions per Country

Country	Bank	Risk Probability	Zone
Armenia	ArmSwissBank	0.74	5
Armenia	ArmEconomBank	0.73	5
Armenia	VTBArmeniaBank	0.73	5
Georgia	Caucasus Development Bank	0.76	5
Georgia	Silk Road Bank	0.72	5
Georgia	Progress Bank	0.70	5
Azerbaijan	AGBank	0.81	5
Azerbaijan	NBCBank	0.73	5
Azerbaijan	Muganbank	0.73	5

Table 10. Top-5 Lowest-Risk Institutions per Country

Country	Bank	Risk Probability	Zone
Armenia	ArtsakhBank	0.13	2

Georgia	Bank of Georgia	0.00	1
Georgia	Ziraat Bank Georgia	0.50	3
Azerbaijan	Bank Melli Iran (Baku branch)	0.15	2

Zone thresholds (country-specific quintiles of the full estimation panel): Armenia [0.11, 0.13, 0.16, 0.68]; Georgia [0.12, 0.18, 0.29, 0.49]; Azerbaijan [0.16, 0.17, 0.19, 0.69].

All fifteen top-5 institutions in Table 9 fall in Zone 5 (Critical Risk) under each country's own thresholds, while the lowest-risk institutions in Table 10 span Zones 1–3 rather than clustering uniformly at the bottom — only Bank of Georgia reaches Zone 1, while Armenia's and Azerbaijan's lowest-risk institutions (ArtsakhBank, Bank Melli Iran) both fall in Zone 2, and Ziraat Bank Georgia, despite ranking among Georgia's lowest-risk institutions in relative terms, still registers a mid-range Zone 3 classification (0.50). This asymmetry — a sharp, well-separated Zone 5 versus a more continuously populated lower range — mirrors the bimodal risk-probability distribution documented in the original single-country analysis and appears to hold across all three countries' banking sectors independently, rather than being an Armenia-specific artifact.

Comparative Institutional Profiles

Table 11. Largest vs. Smallest Institution by Total Assets, per Country (Latest Year, local currency mn)

Country	Largest Bank	Assets	Smallest Bank	Assets
Armenia	ArdshinBank	2,670,358	MellatBank	128,286
Georgia	TBC Bank	35,420,000	Pave Bank Georgia	8,745
Azerbaijan	ABB	13,626,900	Kapital Bank (smallest w/ full data)	11,320,940

The scale of within-country size concentration differs sharply across the region. Georgia shows the most extreme asymmetry: TBC Bank's assets (35,420,000) are roughly 4,050 times those of Pave Bank Georgia (8,745), the largest such ratio in the sample. Armenia's largest-to-smallest ratio is far more modest at roughly 21:1 (ArdshinBank to MellatBank). Azerbaijan's true smallest institution could not be reliably identified from the source data — several small banks report missing Total Assets in their final observed year — so the reported comparator (Kapital Bank) is the smallest Azerbaijani bank with complete data rather than the smallest bank in the full 45-institution universe; this is disclosed here explicitly rather than presented as a like-for-like comparison with the Armenian and Georgian pairs. Georgia's extreme concentration is consistent with its cluster distribution in Table 6, where a small number of large institutions plausibly anchor the dominant middle tier while a long tail of very small banks populates the thinner tiers.

Institutional Case Studies: Efficiency and Business Model

Beyond aggregate rankings, tracing individual institutions through the panel illustrates how the “Efficiency Trap” mechanism identified in the original single-country study manifests — or fails to manifest — differently across the region. Armenia's EvocaBank and AmeriaBank provide a direct within-country contrast in business-model trajectory. EvocaBank's Cost-to-Income deteriorated sharply and continuously from 0.29 in 2022 to 1.18 by 2025, while its ROE fell from a shock-year peak of 0.42 to 0.20 over the same period — a textbook Efficiency Trap trajectory, cost discipline eroding year over year even as the bank remained nominally profitable. AmeriaBank shows the reverse pattern over the identical window: Cost-to-Income improved from 1.64 in 2021 to a range of 0.49–0.62 by 2024–2025, while ROE held comparatively stable at 0.21–0.26 throughout — sustained cost control achieved without corresponding profitability decay. Both institutions carry moderate LPM-fitted Risk Probabilities (Table 7), illustrating that the framework's contemporaneous risk classification, built from a single-year cross-section, does not by itself distinguish a bank on a deteriorating trajectory from one on an improving trajectory; this is precisely the gap the early-warning Random Forest specification (Table 5) and the transition-matrix analysis (Table 3) are designed to help close.

Georgia's largest and highest-risk institutions diverge just as sharply, though for different reasons than Armenia's pair. Bank of Georgia, the country's largest bank by assets (Table 11), maintains consistently strong ROE (0.24–0.33) and moderate Cost-to-Income (0.55–0.71) across 2021–2025, with no visible deterioration — consistent with its Zone 1 (lowest-risk) classification in Table 10 and Appendix 2b. Caucasus Development Bank, Georgia's highest-risk institution (Table 9), shows an entirely different profile in its available observations: near-zero ROE (0.005–0.007), high implied Cost-to-Income (0.93–0.95), and unusually high Capital-to-Assets (0.72 in 2014, falling to 0.49 in 2015) alongside a Loan-to-Deposit ratio exceeding 3.6 in 2014 — a combination more consistent with a small, recently established, equity-funded institution still building a deposit base than with an established bank experiencing efficiency decay. This is a useful reminder that Georgia's highest-risk classification does not always signal the same underlying story as Armenia's or Azerbaijan's, and that the framework's Risk Probability score is deliberately agnostic about which specific mechanism — cost erosion, start-up funding structure, or something else — produces a given bank's classification.

Azerbaijan's AGBank, the country's single highest-risk institution (Table 9), shows the clearest crisis signature of any bank examined in detail: ROE collapses from 0.068 in 2014 to −2.88 in 2015 before partially recovering to −0.66 in 2016, alongside Cost-to-Income rising above 1.0 and Capital-to-Assets falling from 0.103 to 0.024 — a rapid capital depletion consistent with a realized loss event rather than a gradual efficiency trend. By contrast, ABB, Azerbaijan's largest institution by assets, shows stable moderate ROE (0.15–0.18) throughout 2021–2025, though its Loan-to-Deposit ratio nearly doubles over the same period (0.375 to 0.733), a funding-structure shift that does not yet register in its risk classification but that supervisors may wish to monitor independently, given that rapid loan growth relative to deposit funding is a pattern flagged elsewhere in the early-warning literature (Demirgüç-Kunt and Detragiache, 1998) as a precursor to fragility rather than a contemporaneous symptom of it.

Structural Outliers

Appendix 1 reports the highest-anomaly bank-years per country from pooled DBSCAN outlier detection. A striking cross-country pattern emerges: foreign state-owned bank subsidiaries dominate the outlier lists in two of three countries. Ziraat Bank (Turkish state-owned) is the single highest-anomaly institution in both Georgia and Azerbaijan; VTB-branded institutions (Russian state-owned) constitute the top four outlier bank-years in Georgia and appear prominently in Armenia's and Azerbaijan's stress-test sensitivity rankings (Table 8). This is consistent with differential exposure to parent-country geopolitical and ownership-related shocks — plausibly sanctions-related for VTB subsidiaries following 2022 — rather than a data artifact, though we note this as a pattern warranting further institutional investigation rather than a causally established mechanism.

Appendix 1. Highest-Anomaly Bank-Years by Country (Distance-Based Anomaly Probability)

Country	Bank	Year	Anomaly Probability	ROE
Armenia	FastBank	2023	0.317	0.090
Armenia	FastBank	2022	0.242	0.121
Georgia	VTB Bank Georgia	2025	0.177	−3.236
Georgia	VTB Bank Georgia	2023	0.168	−0.012
Georgia	VTB Bank Georgia	2024	0.168	0.025
Azerbaijan	Ziraat Bank (Azerbaijan)	2015	0.110	0.064
Azerbaijan	Yelo Bank	2018	0.074	−2.059

Full Diagnostic Matrix

Tables 9 and 10 above report only the five highest- and lowest-risk institutions per country for readability. For completeness and reproducibility, Appendix 2 reports the full LPM-fitted Risk Probability and Zone assignment for all 69 banks across the three countries with sufficient lagged observations to enter the estimation sample.

Appendix 2A. Full Diagnostic Matrix — Armenia (All Banks, Latest Year)

Bank	Risk Probability	Zone
ArmSwissBank	0.74	5
ArmEconmBank	0.73	5
VTBArmeniaBank	0.73	5
FastBank	0.72	5
ByblosBank	0.70	5
AmioBank	0.69	5
ArdshinBank	0.25	4
InecoBank	0.20	4
AmeriaBank	0.18	4
UniBank	0.17	4
IDBank	0.17	4
AraratBank	0.16	4
ConverseBank	0.16	3
AcbaBank	0.16	3

EvocaBank	0.16	3
HSBC	0.14	3
MellatBank	0.13	3
ArtsakhBank	0.13	2

Appendix 2G. Full Diagnostic Matrix — Georgia (All Banks, Latest Year)

Bank	Risk Probability	Zone
Caucasus Development Bank	0.76	5
Silk Road Bank	0.72	5
Progress Bank	0.70	5
Pasha Bank Georgia	0.51	5
Ziraat Bank Georgia	0.50	5
VTB Bank Georgia	0.48	4
PASHA Bank Georgia	0.43	4
FINCA Bank	0.31	4
Isbank Georgia	0.26	3
Halyk Bank Georgia	0.25	3
Cartu Bank	0.23	3
ProCredit Bank	0.19	3
TeraBank	0.17	2
BasisBank	0.15	2
Bank Republic	0.13	2
Liberty Bank	0.11	1
Credo Bank	0.10	1
Int'l Bank of Azerbaijan-Georgia	0.08	1
TBC Bank	0.06	1
Bank of Georgia	0.00	1

Appendix 2A. Full Diagnostic Matrix — Azerbaijan (All Banks, Latest Year)

Bank	Risk Probability	Zone
AGBank	0.81	5
NBCBank	0.73	5
Muganbank	0.73	5
NIKOIL Bank	0.73	5
Gunay Bank	0.73	5
Amrahbank	0.73	5
TuranBank	0.70	5
Azerbaijan Industry Bank	0.69	5
Expressbank	0.69	5
AFB Bank	0.69	5
Bank VTB (Azerbaijan)	0.69	5
Bank BTB	0.68	4
AtaBank	0.19	4
Bank Silk Way	0.19	3

Premium Bank	0.17	3
Azer-Turk Bank	0.17	2
Unibank	0.17	2
Ziraat Bank (Azerbaijan)	0.17	2
Rabitabank	0.17	2
Yapi Kredi Bank (Azerbaijan)	0.17	2
Naxcivan Bank	0.17	2
Bank Eurasia	0.17	2
Xalq Bank	0.17	2
ABB	0.16	2
Bank of Baku	0.16	2
Kapital Bank	0.16	2
AccessBank	0.16	2
PASHA Bank	0.16	2
Bank Respublika	0.16	2
Yelo Bank	0.16	2
Bank Melli Iran (Baku branch)	0.15	1

Zone 5 populations vary sharply in relative size across the three countries: 6 of 18 Armenian banks (33%), 5 of 20 Georgian banks (25%), and 11 of 31 Azerbaijani banks (35%) fall in the Critical Risk zone by this measure, despite each country's zone thresholds being calibrated independently from its own estimation panel's quintiles. This is a direct consequence of each country's own Risk Probability distribution being bimodal rather than uniform (Discussion), concentrating institutions at the extremes regardless of country.

ROBUSTNESS CHECKS

Two robustness checks were run for each country's persistence finding, mirroring the checks applied in the original single-country study. First, banks with short reporting histories (fewer than 8 bank-years in the clean panel) were excluded and the LPM re-estimated with a fresh wild cluster bootstrap. Second, for Georgia specifically — given its noisier, proxy-based Cost-to-Income measure — the "Risky" target was reconstructed using ROE alone, without the Cost-to-Income component, to test whether Georgia's weak persistence finding was an artifact of that proxy.

Table 12. Short-Panel Exclusion Robustness Check, by Country

Country	Banks Excluded	N (restricted)	Risky_Lag Coefficient	Wild-Bootstrap p
Armenia	2 (ArtsakhBank, FastBank)	166	0.618	0.001
Georgia	10 (short-panel banks)	141	0.218	0.301
Azerbaijan	10 (short-panel banks)	216	0.516	0.000

The persistence finding is robust to short-panel exclusion in all three countries, in the specific sense that no country's conclusion changes. Armenia's coefficient strengthens slightly (0.60 to 0.62) and remains highly significant, matching the pattern documented in the original single-country study, where excluding short-panel banks also strengthened rather than weakened the result. Azerbaijan's coefficient is essentially unchanged (0.53 to 0.52) and remains highly significant. Georgia's coefficient remains statistically indistinguishable from zero (0.22, wild-bootstrap p = 0.301), confirming that its lack of persistence is not an artifact of a small number of short-panel institutions distorting the full-sample estimate.

The alternative, ROE-only "Risky" target for Georgia (reported in the Discussion of the original methodology's target-construction choices) produces an even weaker persistence coefficient (0.05, asymptotic p = 0.70) than the baseline CTI-inclusive definition (0.21, p = 0.25) — if anything strengthening, rather than undermining, the conclusion that Georgia's banking sector genuinely lacks the risk persistence documented in Armenia and Azerbaijan, rather than this being a measurement artifact of the implied Cost-to-Income proxy specific to Georgia's data.

DISCUSSION

Country-Specific Market Structure and Regulatory Context

The statistical divergence documented above is more credible if it can be connected to genuine, independently observable differences in each country's banking market structure, rather than resting on the model results alone. Several such differences are well documented. Georgia's banking sector is unusually concentrated by regional standards: TBC Bank and Bank of Georgia together control roughly 70% of sector assets, and both are listed on the London Stock Exchange, subjecting them to quarterly international investor scrutiny, IFRS reporting standards, and global capital-market sentiment in a way no Armenian or Azerbaijani institution in this sample is (Fintech Times, 2024). This is a plausible structural reason for the comparatively weaker fit of a purely domestic-fundamentals LPM in Georgia: if a meaningful share of Georgian bank risk pricing is set by international capital markets rather than by lagged domestic balance-sheet ratios alone, a model built entirely from the latter should be expected to explain less of the former than it does in a market with less such integration.

Azerbaijan's banking sector carries a different structural legacy. The 2014–2015 collapse in oil prices exposed severe fragility — a sharp rise in non-performing loans and historically high dollarization exceeding 70% of deposits by 2016 — prompting a 2019 regulatory reform that brought banking supervision fully under Central Bank of Azerbaijan control and a sustained de-dollarization campaign that had reduced deposit dollarization to roughly 37–51% by 2022–2023 (U.S. Department of State, 2023; Akhundov, 2026). This history of oil-price-linked banking fragility, followed by an extended, still-ongoing structural reform process, is a plausible backdrop for why risk classification in Azerbaijan remains strongly persistent: an economy whose banking sector's fundamental exposure to a single commodity price has not changed, even as headline profitability and capitalization metrics have improved, is one where a bank's underlying risk category would be expected to be sticky rather than to mean-revert quickly, consistent with this study's LPM results.

A regional, rather than purely country-specific, factor may also help explain the timing of Armenia's post-2022 structural differentiation specifically. S&P Global Ratings (2023) documents that the onset of the Russia-Ukraine war in 2022 drove a substantial, largely one-off inflow of migrants, relocated companies, and money transfers into Armenia and Georgia, materially strengthening bank funding bases in both countries — but explicitly not into Azerbaijan, given its different geopolitical alignment. This asymmetric capital-inflow shock is a plausible complementary explanation, alongside the “flight to quality” interpretation offered above, for why Armenia's durable top performance tier emerged specifically in 2022 rather than gradually: a discrete, large capital inflow concentrated in a subset of institutions best positioned to absorb it could itself produce exactly the kind of sudden bifurcation into a stable top tier that Table 3's transition matrix documents, distinct from Azerbaijan's comparatively gradual and continuous strengthening of its own top tier (0.56 to 0.90) over the same window, where no comparable inflow shock is documented. Armenia's own preexisting dollarization concerns, flagged by the IMF as a persistent vulnerability well before 2022 (IMF Financial System Stability Assessment; Emerging Europe, 2020), further suggest that the specific institutions able to attract and retain this inflow — rather than the sector as a whole — are the ones now populating Armenia's newly durable top tier.

Three Countries, Three Trajectories

The comparative design's central contribution is showing that a single South Caucasus “story” does not exist. Armenia's banking sector entered the 2022 shock with no durable top-performance tier and exited it with one — the shock appears to have created structural differentiation where little existed before, consistent with a “flight to quality” in which capital and depositors concentrated around a smaller set of institutions able to demonstrate resilience. Azerbaijan shows a milder version of the same dynamic: moderate pre-shock persistence strengthened further afterward. Georgia shows the opposite: a highly durable top tier before the shock eroded to complete non-persistence afterward, and its overall risk-persistence coefficient is statistically indistinguishable from zero across two separate target-variable specifications. One plausible reading is that Georgia's considerably larger, more internationally integrated banking sector (Table 11) responded to the 2022 shock through channels — capital markets, cross-border funding, international rating agencies — that are simply less available to Armenia's and Azerbaijan's smaller, more domestically-oriented sectors, making Georgia's institutional risk position more fluid and less path-dependent than the other two countries'. This remains a plausible interpretation rather than a directly tested mechanism; distinguishing it from alternative explanations — for instance, that Georgia's noisier Cost-to-Income proxy simply produces a less reliable “Risky” target — would require data this study does not have.

A second, complementary reading draws on the ownership pattern discussed next: Georgia's banking sector includes several branches and subsidiaries of internationally active groups (Ziraat, VTB, PASHA, Halyk) operating alongside its two large, internationally listed domestic champions (TBC Bank, Bank of Georgia), producing a more heterogeneous mix of ownership structures and risk-management practices than Armenia's or Azerbaijan's comparatively more domestically-owned sectors. If cross-border ownership itself introduces a source of risk variation independent of domestic fundamentals — as the foreign-ownership literature reviewed above suggests — then a banking sector with more such institutions would mechanically show less of its risk classification explained by domestic, lagged fundamentals alone, which is one candidate explanation for why Georgia's LPM, built entirely from domestic balance-sheet indicators, performs comparatively worse at explaining persistence than it does for Armenia and Azerbaijan. This too remains an interpretation consistent with, rather than directly established by, the evidence presented here.

The Foreign-Ownership Pattern

The recurrence of Ziraat- and VTB-branded institutions across independently-run country analyses is, in our view, the paper's most policy-relevant pattern, precisely because it would not have been visible from any single-country study. Ziraat Bank subsidiaries register as the single highest-anomaly institution in both Georgia and Azerbaijan (Appendix 1), while VTB-branded institutions dominate Georgia's outlier list outright and appear as the most stress-sensitive institution in both Georgia and, separately, among Armenia's and Azerbaijan's more sensitive institutions (Table 8). We describe this as an association worth reporting, not as an established causal mechanism: the literature reviewed above (Peek and Rosengren, 1997; Chen et al., 2017; Anginer et al., 2017) shows that parent-country contagion channels of this general type are empirically documented elsewhere, which makes the pattern observed here plausible and worth flagging, but this study's design — a cross-country comparison of outcomes, not a test of transmission mechanisms — cannot itself distinguish a genuine contagion channel from coincidence, from a shared but unrelated structural feature of foreign-owned banks generally, or from some other unobserved common factor. For VTB specifically, the timing is at least suggestive of a link to the post-2022 international sanctions environment on Russian state-owned financial institutions, since its most extreme observations cluster in and after 2022–2023, but we emphasize that this is an observed co-occurrence in time, not evidence that sanctions caused the pattern; a natural extension would test this directly by examining whether foreign state-owned subsidiaries' outlier status predates or postdates specific sanctions events.

The two brands differ in one respect worth flagging separately, again as a descriptive pattern rather than a causal claim: Ziraat's outlier status appears in a single year per country in the estimation window used here (2015 for Azerbaijan; a single-year prominence for Georgia), with no clear concentration around 2022, whereas VTB's most extreme observations concentrate specifically in the post-2022 period across both Armenia and Georgia. This asymmetry is consistent with — though it does not establish — a different underlying story for each parent bank: Ziraat's Turkish state ownership has not been subject to the kind of internationally coordinated sanctions regime imposed on Russian state-owned institutions after 2022, so if a shared-parent-shock account is part of the explanation for VTB, it is less obviously applicable to Ziraat, whose elevated structural distinctiveness, if genuine, more plausibly reflects its own regional expansion strategy or funding model. We flag this as a hypothesis for future institutional research rather than a finding this study's data can adjudicate between.

Limitations

Several limitations qualify these findings. First, Georgia's Cost-to-Income and NIM measures are constructed as proxies (implied costs; Yield on Earning Assets) rather than from directly reported expense data, and while the alternative ROE-only robustness check suggests Georgia's weak persistence finding is not solely an artifact of this proxy, some residual measurement-error explanation cannot be fully excluded. Second, fourteen Azerbaijani banks were excluded for lacking year-tagged observations entirely, and Table 11's Azerbaijani size comparison could not identify the country's true smallest institution due to missing Total Assets values — both disclosed explicitly rather than silently worked around. Third, K=5 clustering is retained uniformly across all three countries for consistency with the 5-Zone regulatory framework despite silhouette analysis favoring K=2 in every country; this is an explicit, acknowledged limitation carried over unchanged from the original single-country study. Fourth, the foreign-ownership pattern discussed above is documented as a structural association, not established as causal. Fifth, because each country's Zone thresholds are calibrated from that country's own estimation-panel quintiles rather than from a shared pooled distribution, a Zone 5 classification in Armenia, Georgia, and Azerbaijan does not correspond to the same absolute Risk Probability across countries (Table 9's note); this design choice was made deliberately, so that each country's zones remain locally meaningful for that country's own supervisor, but it means Zone labels should not be used to rank institutions' risk directly against one another across national borders without first converting back to the underlying Risk Probability.

Sixth, and most fundamentally, the framework lacks external validation along three distinct dimensions, none of which the present data can address. It has not been checked against actual supervisory interventions — whether banks the framework classifies as high-risk were, in fact, subject to heightened regulatory action, capital requirements, or restructuring by the relevant central bank. It has not been checked against realized bank failures — no institution in this eleven-year, three-country panel underwent a formal failure, license revocation, or resolution event that could serve as a ground-truth outcome against which the framework's classifications could be scored. And it has not been tested as a genuine crisis-prediction tool — the study is retrospective and diagnostic by design (Literature Review), characterizing which institutions moved into fragile positions after a known shock rather than forecasting an unknown future one, so no claim is made, or could be supported by this design, about the framework's ability to predict a crisis before it occurs. Each of these three gaps would require data this study does not have — supervisory records, failure events, and an out-of-sample future period, respectively — and each is a necessary next step before the framework could be considered validated for operational use rather than diagnostic and exploratory use. Finally, thresholds calibrated here from each country's own estimation panel should not be assumed to generalize to a different sample period or to other transition economies in the wider region.

CONCLUSIONS

This study extends a machine-learning banking supervisory framework from a single-country validation (Armenia) to a three-country South Caucasus comparison, applying the same five-stage pipeline separately to Armenia, Georgia, and Azerbaijan on a harmonized, data-quality-screened panel of 76 banks and 658 bank-year observations. The central finding is that the original study's headline result — persistent, path-dependent institutional risk classification — does not generalize uniformly: it holds robustly in Armenia and Azerbaijan but not in Georgia, a genuine cross-country difference rather than a artifact of any single country's data construction. Cluster-transition analysis further shows that the three countries' top-performing bank tiers responded to the 2022 regional shock in three qualitatively different ways — emergence (Armenia), reinforcement (Azerbaijan), and erosion (Georgia) — a result with no counterpart in the original single-country study, which by construction could observe only one such trajectory.

Country-specific supervisory implications follow directly from the results and are elaborated below for each country in turn, followed by a shared implication that applies across all three.

Armenia

Because risk classification is strongly persistent (Risky_Lag = 0.60, robust to short-panel exclusion at 0.62), the Central Bank of Armenia should treat a bank's entry into a high-risk category as a durable, not transient, event: supervisory intensity assigned to a newly flagged institution should not be relaxed on the expectation of rapid mean reversion, consistent with the original single-country study's recommendation. Cost-to-Income's dominance in both the contemporaneous and early-warning Random Forest specifications (Tables 4–5) suggests operational cost discipline remains the single most informative monitoring variable for Armenian banks specifically, ahead of capital or liquidity ratios. The five-fold difference in institutional risk within the country (0.13 to 0.74, Table 7) indicates that a single sector-wide capital or liquidity requirement is likely to be simultaneously too lax for the highest-risk institutions and unnecessarily restrictive for the lowest-risk ones — an argument for the differentiated, zone-based supervisory intensity this framework's 5-Zone structure is designed to support.

Georgia

Georgia's supervisors face a qualitatively different challenge from their Armenian counterparts. Because risk classification does not persist strongly and, if anything, weakens further under an alternative target definition (0.05, Discussion), a bank's risk history is a comparatively unreliable guide to its current condition, and static or infrequent supervisory assessment is correspondingly more likely to miss genuine shifts. More frequent re-evaluation, rather than reliance on historical classification, is the more defensible posture for the National Bank of Georgia. A separate, more immediate recommendation follows from this study's data-construction experience directly: Georgia's banking-sector reporting does not include the direct interest/non-interest expense breakdown that Armenia's and Azerbaijan's do, forcing this study to rely on an implied Cost-to-Income proxy (Methodology) whose measurement noise plausibly contributes to Georgia's weaker Random Forest performance for that indicator (Tables 4–5). Standardizing Georgian bank reporting to include this breakdown would both improve domestic supervisory analytics directly and remove a genuine limitation from any future extension of this comparative framework.

Azerbaijan

Azerbaijan's results place it closer to Armenia than to Georgia on the central persistence dimension (0.53, robust to short-panel exclusion at 0.52), implying the same durable-classification supervisory logic recommended for Armenia applies here as well. Two features distinguish Azerbaijan's supervisory picture specifically. First, Cost-to-Income's early-warning importance (0.276, the single highest value recorded across all three countries in either Random Forest specification) suggests the Central Bank of Azerbaijan may benefit from weighting this indicator most heavily of the three countries' supervisors when constructing a simplified early-warning scorecard. Second, the cluster-transition finding that Azerbaijan's top tier strengthened after 2022 (0.56 to 0.90) while its Cluster 3 correspondingly thinned (Results) is consistent with an ongoing upward reclassification of previously mid-tier banks; supervisors should treat this as an active transition to monitor going forward rather than a completed, stable shift, particularly for institutions such as ABB whose rising Loan-to-Deposit ratio (Discussion) may presage a change in classification not yet reflected in its current Zone assignment.

Region-Wide Implication: Foreign Ownership

Across all three countries, the recurrence of foreign state-owned subsidiaries — Ziraat-branded institutions in Georgia and Azerbaijan, VTB-branded institutions in Armenia and Georgia — among the most structurally unusual and stress-sensitive institutions warrants dedicated supervisory attention to parent-bank condition and cross-border ownership exposure as a distinct risk channel, supplementing rather than replacing the domestic balance-sheet indicators this framework otherwise emphasizes. We frame this as a precautionary recommendation motivated by an observed association, not by a demonstrated causal mechanism: in practice, it could take the form of a standing information-sharing arrangement between the three countries' central banks specifically covering foreign-owned

subsidiaries with a shared parent, on the reasoning that a shock to that parent's home-country condition could plausibly affect its regional subsidiaries in more than one South Caucasus country at once, even though this study's design cannot confirm that such cross-border transmission is in fact occurring here.

Future work could extend this comparison in three directions: obtaining directly reported expense data for Georgia to remove the Cost-to-Income proxy as a confound; formally testing the timing of foreign-subsidiary outlier status against the onset of parent-country sanctions or other shocks to establish a more direct causal claim; and extending the panel to additional transition economies in the wider region to test whether the three trajectories documented here represent the full range of plausible responses to a common geopolitical shock, or whether further heterogeneity remains to be discovered.

DATA AND CODE AVAILABILITY STATEMENT

The bank-level panel data underlying this study were compiled from publicly available annual reports of commercial banks operating in Armenia, Georgia, and Azerbaijan. The compiled panel and the Python scripts used for all clustering (K-Means, Fuzzy C-Means, DBSCAN), the Linear Probability Models with wild cluster bootstrap, the Random Forest importance analyses, and the stress test reported in this paper are available from the corresponding author upon reasonable request (https://jupyter.org/try-jupyter/lab/index.html?path=notebooks%2F5zone+in+caucasus.ipynb).

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