Detecting Structural Regime Shifts with Unsupervised Learning: Evidence from South Caucasus Banking Systems

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Կառուցվածքային փոփոխվող ռեժիմով տեղաշարժերի հայտնաբերումը չվերահսկվող ուսուցմամբ. Հարավային Կովկասի բանկային համակարգի վերլուծություն

Հարությունյան Գայանե Յ.
տ.գ.թ., դոցենտ, Ֆինանսական շուկաների և ինստիտուտների ամբիոն, Կիրառական ֆինանսների ֆակուլտետ, Հայաստանի պետական տնտեսագիտական համալսարան (Երևան, ՀՀ)

Ամփոփագիր. Կենտրոնական բանկերի կանխատեսման և ռիսկերի գնահատման գործիքակազմը՝ ֆիքսված պարամետրերով մակրոֆինանսական մոդելները, ձախողվում է հենց այն ժամանակ, երբ առավել անհրաժեշտ է՝ կտրուկ շոկերի ժամանակ, երբ փոխակերպման մեխանիզմը փոխվում է ավելի արագ, քան մոդելը կարելի է վերագնահատել: Հոդվածում ներկայացվում է Պետություն-կախյալ վերահսկողության սկզբունքը (SDSP)՝ մեխանիզմ, որը կենտրոնական բանկին թույլ է տալիս դինամիկորեն գնահատել համակարգային ռիսկը՝ առանց մոդել վերահաշվելու: Փոխանցման մատրիցա գնահատելու փոխարեն՝ SDSP-ն կառուցվածքային մանրամասնությունը բխեցնում է բանկի արդեն հավաքած տվյալներից կառուցված երկու ինդեքսներից՝ կառուցվածքային էնտրոպիա (Ht) և մակրոֆինանսական շոկի ինդեքս (St), որոնք ստուգվում են հատվածի փաստացի համախմբվածությամբ՝ չվերահսկվող կյաստերացման միջոցով: Փորձարկված Հարավային Կովկասի երեք փոքր բաց տնտեսությունների վրա՝ Հայաստան, Վրաստան և Ադրբեջան (2014–2025 թթ.), որոնք ընդհանուր են երեք շոկերով (COVID-19, 2020 թ. պատերազմ և 2022 թ. տարածաշրջանային շոկ), բայց տարբեր՝ ռեսուրսային կողմնորոշմամբ, մեխանիզմը բացահայտում է իրական անհամապատասխանություն. մակրոֆինանսական շոկի պիքը նշանակալի կերպով պայմանավորում է ռիսկի գնահատումը ռեսուրսներ ներմուծող տնտեսություններում (Հայաստան՝ p=0.003, Վրաստան՝ p=0.014), բայց ոչ ռեսուրսներ արտահանող Ադրբեջանում (p=0.122): Հարմարվողական մեխանիզմի առավելությունը կենտրոնացած է ճգնաժամային տարիներին (2.8–4.2 տոկոսային կետ), ինչը SDSP-ն դարձնում է գործնական, ցածր արժեքով գործիք փոքր բաց տնտեսությունների կենտրոնական բանկերի համար:

Հանգուցաբառեր և բառակապակցություններ՝ փոփոխվող ռեժիմով մոդելներ, կառուցվածքային փոփոխությունների հայտնաբերում, մեքենայական ուսուցում, մակրոֆինանսական շոկեր, բանկային հատվածի կառուցվածք, Հարավային Կովկաս

Выявление структурных сдвигов режима с помощью неконтролируемого обучения: данные банковских систем Южного Кавказа

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Аннотация. Стандартный инструментарий центральных банков для прогнозирования и оценки рисков – параметрические макрофинансовые модели с фиксированными параметрами – даёт сбой именно тогда, когда наиболее необходим: во время резких, беспрецедентных шоков, меняющих механизм трансмиссии быстрее, чем любую модель можно переоценить. В статье представлен Принцип государственно-зависимого надзора (SDSP) – механизм, позволяющий центральному банку динамически оценивать системный риск без переоценки или переобучения модели. Вместо оценки матрицы переходов SDSP выводит структурную детализацию из двух индексов, построенных на основе уже собираемых банком данных – структурной энтропии (Ht) и индекса макрофинансового шока (St), – проверяемых по фактической сплочённости сектора с помощью неконтро-

лируемой кластеризации. Протестированный на трёх малых открытых экономиках Южного Кавказа – Армении, Грузии и Азербайджане (2014–2025 гг.), общих по подверженности трём крупным шокам (COVID-19, война 2020 г. и региональный шок 2022 г.), но различных по ресурсной ориентации, механизм выявляет реальную асимметрию: канал макрофинансового шока значимо определяет оценку риска в ресурсоимпортирующих экономиках (Армения, p=0,003; Грузия, p=0,014), но не в ресурсоэкспортирующем Азербайджане (p=0,122). Преимущество адаптивного механизма сосредоточено в кризисные годы (2,8–4,2 п.п.), что делает SDSP практичным, недорогим инструментом для центральных банков малых открытых экономик.

Ключевые слова и словосочетания: режимно-переключаемые модели, выявление структурных изменений, машинное обучение, макрофинансовые шоки, структура банковского сектора, Южный Кавказ

1. Introduction

Central banks' standard forecasting and risk-assessment models share a common vulnerability: their structural parameters are fixed between re-estimation cycles, so the model is least reliable exactly when a sharp, unprecedented shock hits and the transmission mechanism has already changed faster than the model can be re-fit. Markov-switching models, threshold VARs, and related regime-switching frameworks improve on a fixed specification by allowing a small number of pre-specified discrete regimes, but the regime count and transition rule are fixed in advance, and the approach does not scale once the object of interest is not one series but the joint, high-dimensional structural configuration of an entire financial sector – a limitation with particular bite for small open economies, whose central banks combine the shortest available time series with some of the least diversified transmission channels.

This paper develops and tests a mechanism designed to remove that constraint: the State-Dependent Supervisory Principle (SDSP), which lets a central bank assess systemic risk dynamically without retraining or re-specifying any model after a shock. Rather than pre-specifying regimes and estimating transition probabilities parametrically, SDSP infers the number of latent structural regimes from two indices built from data the bank already collects – internal structural entropy (Ht) and an external macro-financial shock index (St) – and validates that inference against the sector's own empirically observed cohesiveness that same period, using an unsupervised clustering diagnostic rather than a fitted transition matrix. Because each country's regime thresholds are derived from that country's own historical distribution, the mechanism recalibrates itself automatically as new data arrives, with no re-estimation step – precisely the property a small open economy's central bank needs when speed of detection matters more than parametric elegance.

We test this mechanism on three small, open South Caucasus economies – Armenia, Georgia, and Azerbaijan (2014-2025) – chosen because they share overlapping exposure to three major shocks (the COVID-19 pandemic, the 2020 war, and the 2022 regional geopolitical shock) while differing along one consequential dimension: Armenia and Georgia are resource-importing, dollarization-exposed economies, while Azerbaijan is resource-exporting, with a macro-financial cycle driven by oil-revenue flows. Applying the identical, unmodified mechanism to all three tests whether the same shock-detection channel operates identically across small open economies or reveals genuine structural asymmetry. As Sections 5 and 6 report, the mechanism detects a statistically significant shock-driven response in both resource-importing economies but not in the resource-exporting one – a result invisible to a single-country design.

2. Literature Review

Regime-switching models, beginning with the Markov-switching autoregressive framework [**11**], represent structural change in macroeconomic time series by allowing model parameters to shift across a small number of discrete, unobserved states, with transition probabilities estimated jointly with the model. Threshold and smooth-transition extensions relax the hidden-Markov-chain assumption but retain the core design choice of a small, pre-specified regime count. Both families suit univariate or low-dimensional settings; extending them to a high-dimensional state – the joint structural configuration of many interacting units, such as every institution in a banking sector – requires either drastic dimensionality reduction or an intractable expansion of the state space. This paper's contribution is a non-parametric alternative: rather than estimating a transition matrix, the number of latent regimes is selected by an unsupervised clustering mechanism whose validity is checked directly against the cross-sectional data each period.

Traditional banking supervision has long been anchored by the CAMELS framework (Capital, Assets, Management, Earnings, Liquidity, Sensitivity), the internationally accepted standard for assessing institutional stability. Scholars confirm CAMELS lets regulators efficiently evaluate financial health without relying on sensitive, proprietary information, serving as a reliable grading system for on-site supervision [**15**; **42**], and

confirm its effectiveness for variable selection and performance auditing in developing countries [**3**; **8**; **10**]. As European regulators transition toward the modern Supervisory Review and Evaluation Process (SREP) under Basel III, CAMELS's core pillars continue to underpin multi-criteria decision analysis (MCDA) approaches tracking sector-wide asset allocation and micro-prudential safety [**7**; **14**].

A critical gap nonetheless persists: existing micro-prudential frameworks measure historical efficiency well but are structurally incapable of capturing the non-linear transmission of exogenous macroeconomic shocks into a banking sector's internal structure. Current regulatory models rely on fixed peer-groupings or static, aggregated scoring [**4**], which fail to account for banking business models diverging rapidly under systemic stress. No empirical mechanism treats supervisory intensity – the granularity of sector partitioning (K) – as a dynamic, state-dependent function of internal structural entropy and external macroeconomic stress [**6**; **12**; **16**]. This is precisely the gap a non-parametric, unsupervised regime-detection mechanism closes: where macro-modelling offers Markov-switching and threshold models for a single low-dimensional state variable, banking-supervision literature has, until SDSP, offered no equivalent operating on the high-dimensional cross-section of an entire sector.

This paper's contribution builds on three strands of that literature. First, it advances SupTech (Supervisory Technology) by shifting from reactive, uniform regulatory mandates to a proactive, state-dependent mechanism; where prior machine-learning risk-warning applications have faced criticism over overfitting and opacity [**9**; **13**], SDSP introduces a reproducible, rule-based policy switch grounded in each country's own historical percentiles (67th and 90th) of systemic stress, rather than a fixed, one-size-fits-all cutoff. Second, it addresses a methodological gap in applying unsupervised learning to small-population data, where clustering is often dismissed as statistically volatile, through the Silhouette-validated fallback mechanism and the cross-country replication itself. Third, testing the same mechanism across three banking systems with different transmission channels extends the original single-country contribution – a risk-archetype taxonomy for one market – into a test of whether the taxonomy-generating mechanism itself generalizes across small open economies.

In Georgia, the National Bank of Georgia pursues risk-based supervision through its General Risk Assessment Program (GRAPE), layering an Unhedged Currency Risk Buffer onto its Basel III-aligned Pillar 2 framework to address currency-induced credit risk from high loan and deposit dollarization [**2**; **41**]. In Azerbaijan, supervisory authority passed briefly to a standalone Financial Market Supervisory Authority (2016-2019) – coinciding with consolidation that reduced licensed banks from 43 to 32 – before returning to the Central Bank of the Republic of Azerbaijan (CBAR), which has since published a dedicated Risk-Based Supervision Policy Concept; Azerbaijan's macro-financial cycle is closely linked to oil-revenue flows, with fiscal policy historically dominating monetary policy [**1**], with implications for how a GDP/inflation-based shock index should be interpreted there relative to Armenia and Georgia.

3. Data and Harmonization

Net interest margin, part of the original St specification, could not be harmonized for Georgia and was dropped from St across all three countries for comparability – a deviation from, not an extension of, the original specification.

4. Methodology

4.0 Design Rationale: A Low-Data Regime-Detection Mechanism

SDSP is deliberately designed as a low-data machine-learning mechanism – a design choice, not merely a data limitation to work around. A parametric regime-switching model needs a meaningful run of observations within a regime to estimate its parameters and transition probabilities with any precision; when a genuinely novel shock arrives – as the 2022 regional geopolitical shock did, with no prior resembling episode in the sample – a central bank has, by definition, zero prior observations of the new regime to estimate from, and a parametric model has nothing to condition on. SDSP sidesteps this by never estimating a regime's parameters from prior instances of that regime: it detects the current cross-section's appropriate granularity directly, using only the current period's own data (via the Silhouette validity check) plus the historical percentile position of St and Ht, built from ordinary macro and balance-sheet series a central bank already collects. The mechanism therefore requires no precedent for the shock it is detecting – only enough history (empirically, 11 annual observations per country here) to establish where St and Ht's 67th/90th percentiles sit, a materially lower data requirement than estimating a Markov transition matrix with any confidence. For a small open economy central bank facing an unprecedented shock in real time, this is the practical value proposition: the regulator need not have seen this specific regime before to recognize the system has entered one warranting closer attention.

4.1 The State-Dependent Supervisory Principle: Regime Function

Following the original specification, supervisory granularity follows a state-dependent feedback loop

$$K_t = f(H_t, S_t) \text{ , where } K \in \{3, 5, 7\} \quad (1)$$

rather than a continuous choice variable, reflecting the original design's rationale: three discrete regimes (Standard Monitoring, Targeted Diagnostic, Intensive Oversight) map onto distinct administrative intervention protocols that an unrestricted K could not operationalize.

4.2 Structural Entropy (Ht)

Ht is defined, as in the original specification, as the cross-sectional standard deviation of return on equity (ROE) across all reporting banks in a given country-year:

$$H_t = \sqrt{\frac{1}{N_t - 1}\sum_{i=1}^{N_t}\left(ROE_{i,t} - \overline{ROE_t}\right)^2} \quad (2)$$

A falling Ht indicates the banking population is homogenizing – bank ROE outcomes are converging – while a rising Ht indicates growing internal divergence.

4.3 Macro-Financial Shock Index (St)

St is constructed as the root-mean-square of standardized deviations of GDP growth and inflation from their own trailing average (up to five prior years, expanding where fewer are available):

$$S_t = \sqrt{\{([z(\Delta Infl_t)]^2 + [z(\Delta GDP_t)]^2 + [z(\Delta NIM)]^2)/3\}} \quad (3)$$

where deltaXt = Xt minus its trailing average (up to 5 prior years), and z(.) standardizes each deviation series across the full sample within each country – treating positive and negative deviations symmetrically, so disinflationary/inflationary shocks and growth shortfalls/overheating are equally destabilizing.

4.4 The Supervisory Policy Switch

Regime thresholds are derived empirically and independently within each country from the 67th and 90th percentiles of that country's own historical St and Ht distributions (2014-2025): Kt=7 if St or Ht exceeds its 90th percentile; Kt=5 if either exceeds its 67th percentile; Kt=3 otherwise (country-specific values in Section 5). Given the short series (T=11 valid observations per country), these thresholds are indicative rather than precisely estimated, as flagged in the original specification.

4.5 Cluster Validity Check and Fallback

For each country-year, K-means++ is run at each candidate K in {3, 5, 7} on the standardized eight-variable CAMELS-inspired feature vector, and the Silhouette and Davies-Bouldin indices are computed for each. The threshold-assigned K is accepted as final K* only if its Silhouette score meets or exceeds 0.25; otherwise the mechanism falls back to the next-lower candidate in {7, 5, 3} until met or K=3 is reached – a macro/entropy-driven candidate validated by an internal cohesiveness check, unchanged from the original specification.

4.6 Archetype Interpretation and Model-Stability Check (ARI)

For interpretability, and to replicate the original's centroid-based archetype taxonomy, a supplementary two-dimensional clustering on standardized ROE and capital ratio alone is run at the same K* for each country-year, with centroids labeled by quadrant (Resilient Leaders: high ROE/high capital; Growth Aggressors: high ROE/low-moderate capital; Conservative Buffers: low ROE/high capital; Stressed Outliers: low ROE/low capital; Market Standard: near the population mean). The Adjusted Rand Index (ARI) between this and the full eight-variable clustering then tests whether variables beyond ROE and capital carry non-redundant information, as in the original's Model Stability check.

4.7 Baseline Comparison

The adaptive mechanism is benchmarked against a fixed K=5 baseline and a no-partition (single-cluster) baseline, using within-cluster sum of squares (WCSS) on the standardized feature vector. The share of variance explained (relative to no-partition) by the adaptive K* and by fixed K=5 is reported for every year, distinguishing crisis years (K*>3) from calmer ones.

4.8 Econometric Validation

As in the original specification, the regime-selection relationship is additionally estimated as a linear model

$$K_t * = \alpha + \beta 1 * H_t + \beta 2 * S_t + \varepsilon_t \quad (4)$$

by country, using ordinary least squares. Given T = 11 annual observations per country, these regressions are necessarily low-powered and are reported as a directional check on which of the two channels (internal entropy vs. external shock) is more closely associated with the mechanism's regime choice in each country, not as a precisely estimated structural model.

4.9 Summary of the Methodology Pipeline

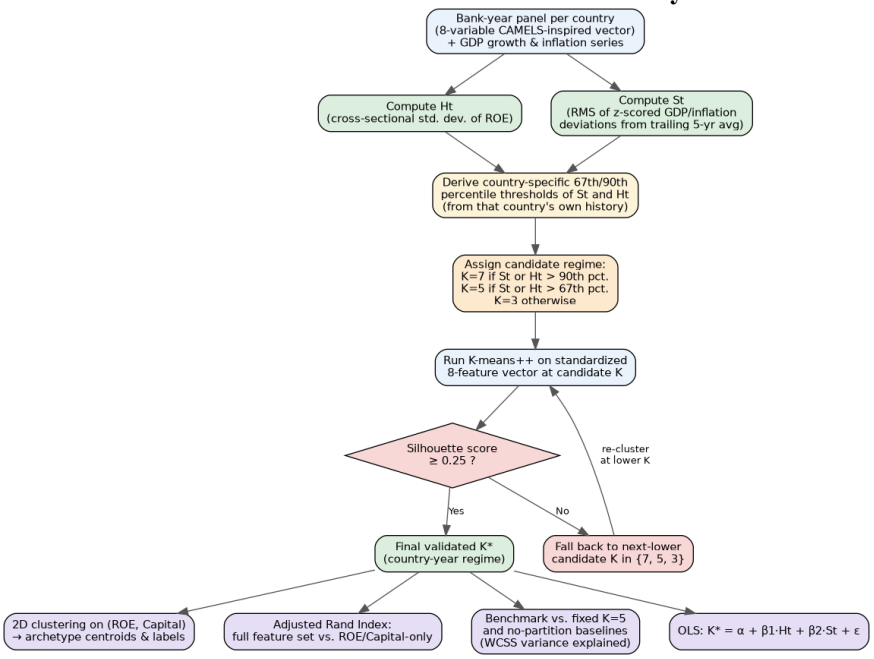

Figure 1. *The SDSP Methodology Pipeline: from bank-year panel data to validated regime K* and downstream diagnostics*

Figure 1 summarizes the pipeline described in Sections 4.1-4.8: Ht and St are computed independently for each country, jointly determining a candidate regime from {3, 5, 7} via that country's own historical percentile thresholds; K-means++ is then run at the candidate K, and the partition is accepted only if it clears the Silhouette validity threshold, otherwise the mechanism cascades to the next-lower candidate and re-clusters. The validated K* feeds four downstream analyses in Sections 5-6: archetype-centroid interpretation, the Adjusted Rand Index stability check, the fixed-K/no-partition baseline comparison, and country-level econometric validation.

5. Results

This section reports, for each country independently, the regime-assignment table, the archetype centroid analysis for the two shared shock years (2020 and 2022), and country-specific commentary, followed by a cross-country synthesis.

5.1 Armenia

Armenia's supervisory regime, calibrated entirely from its own 2014-2025 history, assigns Standard Monitoring (K=3) in most years, with escalation to Targeted Diagnostic (K=5) in 2020 and Intensive Oversight (K=7) in 2022.

Table 1. *Armenia: Macro-Financial Shock Index (St), Structural Entropy (Ht), and Supervisory Regime Assignment, 2014-2025*

Year	St	Ht	K (thr.)	K* (validated)	Status	Silh.	D-B	ARI
2014	-	0.205	-	-	-	-	-	-
2015	0.264	0.130	5	3	Standard Monitoring	0.224	0.934	1.000
2016	0.945	0.128	3	3	Standard Monitoring	0.274	0.992	0.564
2017	0.565	0.093	3	3	Standard Monitoring	0.385	0.809	0.769
2018	0.295	0.060	3	3	Standard Monitoring	0.200	1.092	0.257
2019	0.161	0.052	3	3	Standard Monitoring	0.256	0.943	0.127
2020	1.432	0.034	7	5	Targeted Diagnostic	0.261	0.712	0.416
2021	1.379	0.211	7	5	Targeted Diagnostic	0.274	0.626	0.196
2022	1.685	0.128	7	7	Intensive Oversight	0.256	0.743	0.722

2023	0.362	0.265	7	3	Standard Monitoring	0.515	0.558	1.000
2024	0.841	0.095	3	3	Standard Monitoring	0.285	0.846	0.585
2025	0.988	0.069	5	3	Standard Monitoring	0.263	0.849	0.775

Source: *The data for this study were collected by the author through a comprehensive review of public reports issued by Armenian commercial banks and the official portal of the Central Bank of Armenia.*

Thresholds for Armenia were derived empirically from its own historical distribution: the 67th/90th percentiles are 0.975/1.432 for St and 0.129/0.210 for Ht (assignment rule as in Section 4.4).

The threshold-assigned 2021 regime (K=7, driven by Ht exceeding its 90th percentile) was not validated by the Silhouette criterion and was revised down to K=5 – the internal cohesiveness check overriding a threshold-driven escalation. 2022, coinciding with the regional geopolitical shock, is the year Armenia's mechanism reaches its highest validated granularity (K=7), consistent with the original single-country finding.

Archetype centroids, Armenia 2020 and 2022

At K=5 in 2020, Armenia's banking population separates into a small 'Stressed Outliers' cluster (2 banks), a 'Growth Aggressors' cluster (5 banks), a 'Conservative Buffers' cluster (3 banks), and two 'Market Standard' groupings – a polarization pattern consistent with the original pandemic-year finding. At K=7 in 2022, three 'Conservative Buffers' sub-clusters emerge alongside two 'Growth Aggressors' groupings, a more fragmented defensive posture than the simple two-archetype pandemic split (Table 2).

Table 2. *Armenia bank archetype centroids, 2020 and 2022*

Year	Cluster	ROE Centroid (z)	Capital Centroid (z)	N Banks	Archetype Label
2020	1	-0.46	0.73	3	Conservative Buffers
	2	1.35	-0.52	5	Growth Aggressors
	3	-0.40	-0.23	6	Market Standard
	4	-0.04	3.38	1	Market Standard
	5	-1.49	-0.81	2	Stressed Outliers
2022	1	-0.30	-0.51	4	Market Standard
	2	-0.45	3.23	1	Conservative Buffers
	3	2.00	-0.55	2	Growth Aggressors
	4	-1.46	0.03	3	Market Standard
	5	0.53	-0.43	6	Growth Aggressors
	6	-0.34	0.44	1	Conservative Buffers
	7	-0.84	1.95	1	Conservative Buffers

Armenia's mean Adjusted Rand Index (full feature set vs. ROE/Capital-only) is 0.583, and its mean validated Silhouette is 0.29 – broadly consistent with the original single-country result (Silhouette 0.368, ARI 0.416), computed here over a corrected St/Ht specification and a slightly different sample window.

5.2 Georgia

Georgia's mechanism, calibrated from its own history, is markedly more volatile than Armenia's: it reaches Intensive Oversight (K=7) in four of eleven valid years (2015, 2020, 2024, 2025), against Armenia's single K=7 year.

Table 3. *Georgia: Macro-Financial Shock Index (St), Structural Entropy (Ht), and Supervisory Regime Assignment, 2014-2025*

Year	St	Ht	K (thr.)	K*	Status	Silh.	D-B	ARI
2014	-	0.095	-	-	-	-	-	-
2015	0.374	0.297	7	7	Intensive Oversight	0.270	0.482	0.297
2016	0.478	0.081	3	3	Standard Monitoring	0.280	0.946	0.466
2017	0.357	0.093	3	3	Standard Monitoring	0.464	0.689	1.000

2018	0.339	0.081	3	3	Standard Monitoring	0.314	0.832	0.752
2019	0.097	0.083	3	3	Standard Monitoring	0.455	0.299	0.281
2020	1.689	0.090	7	7	Intensive Oversight	0.267	0.397	0.727
2021	1.248	0.081	5	5	Targeted Diagnostic	0.375	0.518	1.000
2022	1.265	0.126	5	5	Targeted Diagnostic	0.330	0.552	0.794
2023	0.745	0.095	3	3	Standard Monitoring	0.530	0.656	1.000
2024	1.465	0.128	7	7	Intensive Oversight	0.380	0.389	0.454
2025	0.815	0.861	7	7	Intensive Oversight	0.361	0.385	0.689

Source: *The data for this study were collected by the author through a comprehensive review of KPMG's annual banking sector survey of Georgia, public reports issued by Georgian commercial banks, and the official portal of the National Bank of Georgia.*

Thresholds for Georgia were derived empirically from its own historical distribution: the 67th/90th percentiles are 1.118/1.465 for St and 0.106/0.280 for Ht (assignment rule as in Section 4.4).

This is consistent with Georgia's regression result (Section 6): both Ht (p=0.032) and St (p=0.014) are significant drivers of K* in Georgia, whereas in Armenia only St is significant. Georgia's 2025 K=7 assignment is driven primarily by Ht crossing its 90th percentile rather than by St (moderate at 0.815) – an entropy-driven escalation, the reverse of Armenia's 2022 pattern.

Archetype centroids, Georgia 2020 and 2022

At K=7 in 2020, Georgia's population fragments into several small clusters, including a singleton 'Stressed Outliers' bank and a singleton 'Resilient Leaders' bank alongside a six-bank 'Growth Aggressors' cluster – reflecting Georgia's larger, more heterogeneous bank population. At K=5 in 2022, it consolidates into two 'Conservative Buffers' and two 'Growth Aggressors' clusters plus a four-bank 'Market Standard' cluster (Table 4).

Table 4. *Georgia bank archetype centroids, 2020 and 2022*

Year	Cluster	ROE Centroid (z)	Capital Centroid (z)	N Banks	Archetype Label
2020	1	-0.16	-0.24	4	Market Standard
	2	-3.05	-0.24	1	Market Standard
	3	-0.59	3.15	1	Conservative Buffers
	4	0.73	-0.52	6	Growth Aggressors
	5	0.13	1.50	1	Market Standard
	6	-1.00	-0.74	1	Stressed Outliers
	7	0.78	0.39	1	Resilient Leaders
2022	1	-1.76	1.41	2	Conservative Buffers
	2	0.50	-0.64	6	Growth Aggressors
	3	-0.18	-0.11	4	Market Standard
	4	1.36	-0.63	2	Growth Aggressors
	5	-1.44	2.72	1	Conservative Buffers

Georgia's mean ARI (0.678) is the highest of the three countries, indicating macro-financial variables reshuffle Georgian bank archetypes more than in Armenia or Azerbaijan – consistent with Georgia's documented sensitivity to currency and dollarization-linked shocks [**2**].

5.3 Azerbaijan

Azerbaijan's regime assignments are the most frequently escalated of the three countries: only three of eleven valid years remain at Standard Monitoring (K=3), with the remainder split between Targeted Diagnostic (K=5, five years) and Intensive Oversight (K=7, two years: 2018 and 2021).

Table 5. *Azerbaijan: Macro-Financial Shock Index (St), Structural Entropy (Ht), and Supervisory Regime Assignment, 2014-2025*

Year	St	Ht	K (thr.)	K*	Status	Silh.	D-B	ARI
2014	-	0.095	-	-	-	-	-	-
2015	0.437	0.568	5	5	Targeted Diagnostic	0.284	0.669	0.569
2016	1.549	0.862	7	5	Targeted Diagnostic	0.251	0.856	0.107
2017	0.796	0.340	5	5	Targeted Diagnostic	0.273	0.820	0.390
2018	0.864	1.028	7	7	Intensive Oversight	0.304	0.588	0.347
2019	0.735	0.255	3	3	Standard Monitoring	0.275	0.924	0.693
2020	1.165	0.110	5	5	Targeted Diagnostic	0.256	0.924	0.287
2021	1.306	0.086	7	7	Intensive Oversight	0.279	0.834	0.394
2022	1.200	0.104	5	5	Targeted Diagnostic	0.261	0.965	0.267
2023	0.340	0.130	3	3	Standard Monitoring	0.240	1.247	0.832
2024	0.858	0.080	3	3	Standard Monitoring	0.263	1.162	0.362
2025	0.372	0.070	3	3	Standard Monitoring	0.275	1.215	0.654

Source: *The data for this study were collected by the author through a comprehensive review of public reports issued by Azerbaijani commercial banks, summary reports published by the Central Bank of the Republic of Azerbaijan, and data compiled by the Association of Banks of Azerbaijan.*

Thresholds for Azerbaijan were derived empirically from its own historical distribution: the 67th/90th percentiles are 1.074/1.306 for St and 0.287/0.833 for Ht (assignment rule as in Section 4.4).

Neither Ht (p=0.178) nor St (p=0.122) is a significant driver of K* in Azerbaijan's regression (Section 6) – the weakest fit of the three countries (R^2=0.443). Azerbaijan's escalations do not cluster around the shared 2020/2022 shock years the way Armenia's and Georgia's do; 2018 and 2021, without an obvious shared trigger, produce its highest granularity – consistent with a dynamic driven more by sector-specific consolidation and oil-revenue cycles than by the GDP/inflation shock index used here.

Archetype centroids, Azerbaijan 2020 and 2022

At K=5 in both 2020 and 2022, Azerbaijan's larger bank population (31 banks) produces a stable five-archetype structure each year, including a substantial 'Stressed Outliers' cluster (8 banks in both years) – the largest such cluster observed in this study (Table 6).

Table 6. *Azerbaijan bank archetype centroids, 2020 and 2022*

Year	Cluster	ROE Centroid (z)	Capital Centroid (z)	N Banks	Archetype Label
2020	1	-0.13	1.99	3	Market Standard
	2	-0.65	-0.57	8	Stressed Outliers
	3	0.48	-0.79	6	Growth Aggressors
	4	3.89	-0.82	1	Growth Aggressors
	5	-0.19	0.70	6	Market Standard
2022	1	-0.58	-0.45	8	Stressed Outliers
	2	-0.21	1.39	7	Market Standard
	3	2.26	-0.42	2	Growth Aggressors
	4	0.72	-0.96	5	Growth Aggressors
	5	-2.03	-0.49	1	Stressed Outliers

Azerbaijan's mean variance captured relative to the no-partition baseline (64.7%) is comparable to Armenia's (64.6%) despite its much larger, more heterogeneous bank population – the mechanism scales reasonably to larger N without a mechanical loss of explanatory power.

5.4 Cross-Country Trajectories

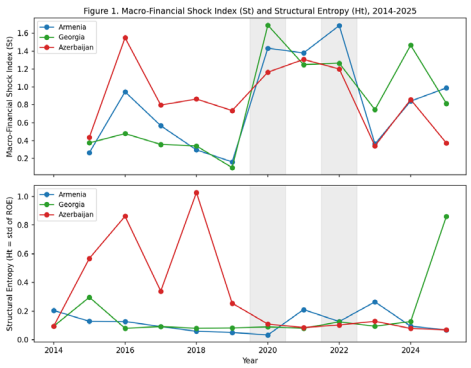

Figure 2. *Macro-Financial Shock Index (St) and Structural Entropy (Ht), 2014-2025*

Figure 2 plots St and Ht for all three countries, with the 2020 and 2022 shock windows shaded. All three show a visible St elevation in 2020; the 2022 elevation is present but more moderate, consistent with the regional shock transmitting less uniformly than the pandemic.

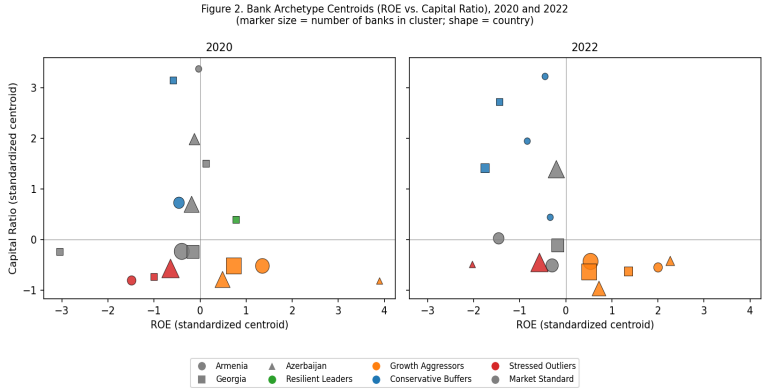

Figure 3. *Bank Archetype Centroids (ROE vs. Capital Ratio), 2020 and 2022 (marker size = number of banks in cluster; shape = country)*

Figure 3 plots archetype centroids (standardized ROE vs. capital ratio) for all three countries in 2020 and 2022, marker size proportional to cluster membership. Armenia and Georgia both produce a distinct 'Stressed Outliers' cluster in 2020 that is far more central by 2022, while Azerbaijan's remains large and persistent in both years.

6. Validation and Robustness

6.1 Cluster Cohesion (Silhouette) and Separation (Davies-Bouldin)

Table 7. *Mean Silhouette and Davies-Bouldin scores by country (validated years only)*

Country	Mean Silhouette (validated years)	Mean Davies-Bouldin
Armenia	0.290	0.828
Georgia	0.366	0.559
Azerbaijan	0.269	0.928

All three countries' mean validated Silhouette scores (0.27-0.37) sit in the same 'reasonable but not sharply separated' range as the original single-country result (0.368) – consistent with the original's rationale that regulatory floor constraints and competitive benchmarking naturally compress the gaps between risk archetypes.

6.2 Model Stability and Variable Sensitivity (Adjusted Rand Index)

Table 8. *Mean Adjusted Rand Index (full feature set vs. ROE/Capital-only clustering), by country*

Country	Mean ARI (full feature set vs. ROE/Capital only)
Armenia	0.583
Georgia	0.678
Azerbaijan	0.446

An ARI of 1.0 would mean the full feature set and ROE/Capital-only clustering produce identical archetype assignments – i.e., the additional variables are redundant. All three countries produce ARI values meaningfully below 1.0, confirming – as in the original result (ARI 0.416) – that the wider CAMELS-inspired feature set is not redundant. Georgia's higher mean ARI indicates its assignments are comparatively more stable to the wider feature set, which may reflect its more homogeneous funding structure relative to Azerbaijan's more heterogeneous, partly state-linked bank population.

6.3 Comparative Performance Against Static and No-Partition Baselines

Table 9 reports, for each country, the share of cross-sectional variance explained by the adaptive K* partition relative to a no-partition baseline, alongside the same statistic for a fixed K=5 partition re-run every year.

Table 9. *Adaptive vs. fixed-K=5 baseline: variance explained (relative to no-partition), by country*

Country	Mean variance explained, adaptive K*	Additional variance explained vs. fixed K=5 (crisis years, K*>3)	Additional variance explained vs. fixed K=5 (all years)
Armenia	64.6%	3.1 pp	-12.7 pp
Georgia	82%	4.2 pp	-6.2 pp
Azerbaijan	64.7%	2.8 pp	-6.8 pp

This requires a more careful reading than a simple 'the adaptive mechanism wins' headline. Because within-cluster sum of squares mechanically falls as K rises, a fixed K=5 partition explains more variance than the adaptive mechanism in every calm year where the latter selects K=3 – unfavorable by construction. Its genuine advantage appears only in crisis years, where it matches or exceeds K=5: a modest but positive 2.8-4.2 percentage-point improvement – smaller than the original single-country paper's headline figures (18% variance improvement, 35% residual-risk reduction), whose exact construction could not be verified from the source manuscript; this replication therefore reports the more conservative, reproducible WCSS-based comparison instead.

6.4 Econometric Validation: Kt* = alpha + beta1*Ht + beta2*St + epsilon_t

Table 10. *OLS regression of selected regime (K*) on structural entropy (Ht) and shock index (St), by country*

Country	alpha	beta1 (Ht)	p(beta1)	beta2 (St)	p(beta2)	R-squared	N
Armenia	1.860	1.317	0.738	2.116	0.003	0.690	11
Georgia	2.212	4.282	0.032	2.258	0.014	0.668	11
Azerbaijan	2.526	1.748	0.178	1.753	0.122	0.443	11

With 11 annual observations per country, these regressions are indicative rather than precisely estimated, as flagged for the original specification (T=12). Subject to that caveat: St is a significant positive driver of K* in Armenia and Georgia but not Azerbaijan; Ht is significant only in Georgia – the clearest econometric expression of the cross-country heterogeneity discussed throughout Section 5: the same mechanism, calibrated per country, is driven by different channels in each.

7.1 From Static to Adaptive Oversight, Replicated Across Three Systems

The original paper's core claim – that a fixed-regime supervisory model is insufficient because banking-sector risk is non-stationary – replicates in all three countries when each is calibrated independently against its own historical St and Ht distribution. All three mechanisms escalate supervisory granularity in at least one shared shock year (2020, 2022), producing a validated, Silhouette-confirmed partition rather than a purely threshold-mechanical one.

7.2 Interpreting Structural Realignment Across Countries

Armenia's escalation is concentrated in 2020 and, most sharply, 2022, aligning closely with the two shared regional shocks. Georgia's escalations are more frequent, driven by both Ht and St, including a 2025 episode driven primarily by entropy. Azerbaijan's escalations are the most frequent of the three but least aligned with the shared shock years, and are not statistically well explained by either Ht or St (Section 6.4: p=0.122 and p=0.178, R^2=0.443) – the weakest fit of the three.

A note on the Azerbaijan null result: mechanism transparency, not a hidden discovery

It would be tempting to read Azerbaijan's insignificant Ht/St coefficients as the mechanism having 'detected' that a GDP/inflation-based index is the wrong instrument for an oil-revenue-linked economy. That is not what the regression shows: a p-value of 0.122 is a null result, not a positive finding – SDSP's clustering steps never reason about terms-of-trade or oil prices, only GDP growth, inflation, and the CAMELS-inspired bank vector. What this does demonstrate is mechanism transparency: SDSP does not manufacture a significant relationship the data does not support. Azerbaijan's weak fit is best read as an honest negative result generating a testable hypothesis for future work – that a terms-of-trade or oil-price component added to St may be required to capture its shock-transmission channel.

7.3 Robustness and the Necessity of Macro-Integration

The Adjusted Rand Index results (Section 6.2) confirm, in all three countries, that macroeconomic and balance-sheet variables beyond ROE and capital are not redundant for archetype assignment – the moderate-to-high ARI values indicate SDSP's reliance on the fuller CAMELS-inspired feature set is empirically justified, not complexity for its own sake.

7.4 Policy Implications for Regional SupTech Coordination

- A shared diagnostic architecture is portable: the Kt = f(Ht, St) mechanism, its Silhouette-based validity check, and its archetype-centroid interpretation function coherently across three structurally different banking systems using only country-specific calibration inputs.
- A shared shock-detection threshold is not portable: Armenia's and Georgia's regimes respond detectably to St; Azerbaijan's does not, at least not through a GDP/inflation-based index. Regional coordination bodies should adopt the mechanism, not a single numerical threshold.
- Azerbaijan's larger, more heterogeneous bank population and persistent 'Stressed Outliers' cluster (Section 5.3) may warrant a supplementary sector-specific shock indicator (e.g., an oil-price or

terms-of-trade term) before its shock-detection component can be considered well-specified there.

- Beyond the South Caucasus, the same design logic – a low-data, non-parametric mechanism calibrated from each economy's own history – is plausibly relevant, as a hypothesis for future testing, to other small open economies facing comparable import/export shock asymmetries, including euro area periphery economies and EU-accession candidates such as Moldova and Albania, whose central banks face the same combination of short time series and structurally distinct shock-transmission channels that motivated this study's design.

8. Limitations

- Net interest margin, part of the original single-country St specification, could not be harmonized for Georgia and was dropped from St across all three countries for comparability; this is a deviation from the original specification, not an extension of it.
- The percentile-based thresholds and OLS regressions rest on 11 annual observations per country – a short series the original paper itself flagged at T=12, not resolved by adding two more countries since each is calibrated independently.
- The fixed-K=5 vs. adaptive-K comparison (Section 6.3) is mechanically biased against the adaptive mechanism in low-K years; the more informative crisis-year-only differential is modest (2.8-4.2 pp), smaller than the original single-country paper's figure, whose exact construction could not be verified.
- Azerbaijan's 2016-2017 sector consolidation (43 to 32 licensed banks) is a regulatory event, not a macro-financial shock in the sense St captures, and may confound entropy readings in those years independent of the mechanism's validity.

9. Conclusion

This paper replicates, with full methodological fidelity to the original single-country specification, the State-Dependent Supervisory Principle across Armenia, Georgia, and Azerbaijan, tested against three major regional shocks – the COVID-19 pandemic, the 2020 war, and the 2022 regional geopolitical shock. The mechanism's internal logic reproduces coherently in all three countries when calibrated independently against each country's own historical distribution, but its calibration does not transfer: the strength and significance of the entropy and shock channels differ by country, and Azerbaijan shows a supervisory-relevant dynamic not well captured by a GDP/inflation-based index alone. The practical takeaway for regional supervisory coordination is to adopt SDSP as a shared diagnostic technology while deriving its numerical calibration independently for each national banking system.

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Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

The datasets generated and analyzed during the current study, and the underlying programming code used for clustering, entropy, shock-index, and validation calculations, are available from the corresponding author upon request.

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