Evaluating Structural Cross-Border E-Commerce Market Attractiveness in the Eurasian Economic Union for Chinese Firms: An Entropy–TOPSIS Analysis Using Multi-Source Public Data

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Abstract. Cross-border e-commerce market selection in the Eurasian Economic Union (EAEU) requires comparison of host markets that differ in market capacity, digital readiness, trade integration, and macroeconomic stability. This study constructs a reproducible structural screening index for Chinese firms from eight public indicators using Entropy–TOPSIS. The Chinese-firm perspective defines the intended decision context: the index compares structural host-market conditions before bilateral and firm-specific due diligence. The 2022–2024 means reported in the paper are frozen as the exact computational matrix; GDP and secure-server intensity are log transformed before normalization. The baseline ranks the Russian Federation, Belarus, Kazakhstan, Armenia, and the Kyrgyz Republic. Equal weighting reverses the top two. In 50,000 log-weight perturbations at s = 0.20, the Russian Federation ranks first in 91.39% of draws. Preprocessing sensitivity preserves the Russian Federation–Belarus upper pair and the Kyrgyz Republic's fifth position, while the Kazakhstan–Armenia ordering changes under some transformation specifications. Leave-one-indicator-out and correlation diagnostics further characterize single-criterion sensitivity and criterion overlap. The index is intended for first-stage market screening rather than causal forecasting or automatic entry choice.

Keywords: cross-border e-commerce, Eurasian Economic Union, market attractiveness, Entropy-TOPSIS, multi-criteria decision making, international market selection

1 Introduction

Cross-border e-commerce (CBEC) reduces some traditional barriers to internationalization but does not eliminate market-selection risk. EAEU members differ substantially in economic scale, purchasing power, digital connectivity, trade openness, and macroeconomic stability. The EAEU has also continued to formalize foreign e-commerce governance through Customs Code amendments and related

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decisions [8], while the Eurasian Economic Commission (EEC) has discussed sustainable EAEU-China cross-border e-commerce development [9]. These developments make comparable country screening relevant, but they do not remove market-level heterogeneity.

CBEC decision studies cover business-environment evaluation, location and warehouse deployment, partner selection, platform choice, and logistics-provider selection [1]–[6]. Entropy–TOPSIS has been applied to China's provincial CBEC business environment [1], while related MCDM studies rank platforms and logistics partners rather than national host markets [5], [6]. What remains less developed is a reproducible country-level screen of all five EAEU members under a common recent data window with explicit analysis of ranking uncertainty. This study addresses that gap through an auditable EAEU-wide screening design built on a frozen public-data matrix, transparent indicator construction, and robustness checks covering alternative weights, stochastic weight perturbation, indicator removal, criterion overlap, and preprocessing choices. The contribution therefore lies in a reproducible country-level decision-support design and explicit characterization of ranking stability under a common MCDM framework.

Three questions guide the analysis: RQ1, how do the five EAEU members compare under a common structural CBEC market-attractiveness index? RQ2, which indicators receive the largest data-driven weights? RQ3, how stable is the ordering under alternative modeling and weighting assumptions? The contribution is a transparent EAEU-wide screening design that (i) reports the exact frozen computational matrix, (ii) distinguishes structural host-market conditions from bilateral China-specific advantage, and (iii) evaluates ranking stability through equal weighting, three weight-perturbation magnitudes, leave-one-indicator-out analysis, criterion-correlation diagnostics, and preprocessing sensitivity. The output is a first-stage decision-support screen rather than a firm-performance forecast or automatic entry recommendation.

2 Related Work and Research Design

2.1 Cross-Border E-Commerce Market Selection

CBEC market entry is multi-attribute. Panova et al. connect e-commerce location with shipping and trade conditions [4]; Liu et al. examine overseas-warehouse deployment [2]; and Chen et al. model B2B partner selection [3]. More recent MCDM applications use different decision units: Zhou et al. evaluate 31 Chinese provinces using an Entropy-TOPSIS business-environment system [1], Jiang et al. rank three import e-commerce platforms using DANP-TOPSIS [5], and Ma and Wang prioritize logistics partners using hybrid group MCDM [6]. In contrast, this study's alternatives are the five EAEU member states. Its indicators are harmonized public country statistics aggregated over 2022–2024, and its robustness analysis evaluates weight scenarios, stochastic perturbation, indicator deletion, criterion overlap, and preprocessing sensitivity. This design moves beyond a single deterministic ranking by

providing an auditable country-level screening result together with explicit evidence on where the ordering is stable and where it remains assumption-sensitive.

2.2 Why an EAEU-Wide Screening Index

The EAEU Digital Agenda emphasizes interoperable digital platforms, cross-border electronic identification, shared infrastructure, and digital trade procedures [7], but regional integration does not imply homogeneous national operating conditions. In this study, attractiveness for Chinese firms is operationalized as the structural host-market component relevant to a prospective entrant: market capacity, purchasing power, digital access and infrastructure, external integration, and macroeconomic stability. The Chinese-firm perspective defines the decision user and the sequence of use: the structural screen prioritizes EAEU markets before China-specific bilateral and firm-level due diligence on product demand, tariffs and certification, platform access, payments, logistics, compliance, and firm capabilities. This interpretation is consistent with EAEU–China e-commerce engagement [9] while keeping the composite score comparable across all five host markets. The overall analytical workflow, from the frozen public-data matrix through preprocessing, entropy weighting, TOPSIS ranking, and robustness diagnostics, is summarized in Fig. 1.

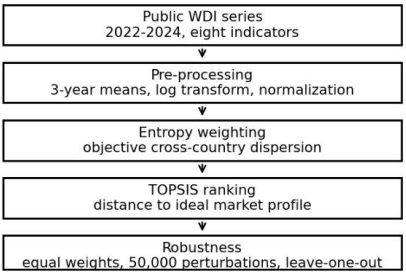


Fig. 1. Analytical workflow for constructing and stress-testing the EAEU structural market-attractiveness ranking.

3 Data and Methodology

3.1 Data Window and Indicator System

The source layer contains complete 2022–2024 observations for each selected indicator, and arithmetic means reduce dependence on a single year. The eight criteria operationalize five structural dimensions: market capacity (GDP), purchasing power (GDP per capita, PPP), digital access and infrastructure (Internet users, mobile subscriptions, and secure Internet servers), external integration (trade and FDI inflows), and macroeconomic stability (CPI inflation). The series were obtained from World Bank World Development Indicators (WDI) on August 10, 2026 [10]; WDI metadata identify the originating source families listed in Table 1. No missing-value

imputation is used. For exact computational reproducibility, each three-year mean is frozen at the precision shown in Table 2 before transformation or normalization. Table 2 therefore constitutes the exact computational input matrix used by the released script, and Supplementary Data S1 stores the same matrix in machine-readable form.

Table 1. Structural indicator system and public data origins

Code	Indicator	Dir.	Origin
NY.GDP.MKTP.CD	GDP, current US$	+	NSO/WB/OECD
NY.GDP.PCAP.PP.CD	GDP per capita, PPP	+	ICP/OECD/IMF
IT.NET.USER.ZS	Internet users	+	ITU
IT.CEL.SETS.P2	Mobile subscriptions	+	ITU
IT.NET.SECR.P6	Secure Internet servers	+	Netcraft/WB
NE.TRD.GNFS.ZS	Trade, percent GDP	+	NSO/WB/OECD
BX.KLT.DINV.WD.GD.ZS	FDI inflows, percent GDP	+	IMF/WB/UNCTAD
FP.CPI.TOTL.ZG	CPI inflation, annual percent	-	IMF

Table 2 is the frozen computational decision matrix. GDP is in billions of current U.S. dollars; PPP is GDP per capita in thousands of current international dollars; Internet is the population share using the Internet; mobile is subscriptions per 100 people; servers are secure Internet servers per million people; and trade, FDI, and inflation are percentages. The values shown in Table 2 are used directly by Code S1, which removes the reproducibility ambiguity associated with hidden higher-precision source values.

Table 2. Frozen computational input matrix, 2022-2024

Market	GDP	PPP	Net	Mob.	Server	Trade	FDI	Infl.
Armenia	23.2	21.2	79.5	133.3	1258	125.8	2.64	3.6
Belarus	74.9	30.8	91.8	129.5	11652	126.6	2.38	8.7
Kazakhstan	259.6	38.5	92.9	126.6	5891	62.6	1.72	12.7
Kyrgyz Rep.	15.2	7.4	89.1	107.7	919	132.1	0.97	9.9
Russian Fed.	2175.1	44.3	92.3	178.5	23216	41.2	-0.88	9.3

3.2 Pre-Processing and Entropy Weights

GDP and secure-server intensity are strongly right-skewed across the five markets, so the baseline specification applies ln(1+x) to these two variables before normalization. Benefit indicators use (1); inflation is the sole cost indicator and uses (2).

Normalization is performed across the five EAEU alternatives after the frozen 2022–2024 aggregate matrix is formed. The transformation preserves within-indicator ordering and maps all criteria to a common zero-one scale. To assess sensitivity to this preprocessing choice, the full Entropy–TOPSIS procedure is additionally evaluated under four transformation specifications: the baseline GDP-and-server log transformation, no log transformation, GDP-only log transformation, and server-only log transformation. These alternatives are used as robustness diagnostics and do not retune the baseline specification.

$$z_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{1}$$

$$z_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{2}$$

For m=5 alternatives,$p_ij = z_ij$ divided by the column sum of z_j; when $p_ij = 0$, the term $p_ij ln(p_ij)$ is defined as zero. Shannon entropy and the normalized information-utility weight are then calculated by (3) [11]. The factor $1/ln(m)$ places e_j on the zero-one interval, and the weights sum to one. These are dispersion weights: they quantify how strongly each indicator differentiates the five observed markets rather than how strongly a manager ought to value that criterion. Preference uncertainty and criterion redundancy are therefore examined separately.

$$e_j = -\frac{1}{\ln m} \sum_i p_{ij} \ln p_{ij}, \quad w_j = \frac{1 - e_j}{\sum_k (1 - e_k)} \tag{3}$$

3.3 TOPSIS and Robustness Tests

TOPSIS evaluates each country by its distance from a positive ideal and a negative ideal [12], [13]. Using the same min-max-normalized matrix,$v_ij = w_j z_ij$. The positive and negative ideals are the columnwise maximum and minimum of V, respectively; $D_i +$ and $D_i -$ are the corresponding Euclidean distances. The closeness coefficient is given by (4), with larger values indicating a profile closer to the best observed combination within the five-market comparison set.

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{4}$$

Five robustness diagnostics are reported. First, equal-weight TOPSIS fixes every criterion at 1/8. Second, Monte Carlo perturbation uses 50,000 draws and seed 20260810. For each draw, $w'j = wjexp(\varepsilon j)$, where εj independently follows N(0, s²), and the perturbed weights are renormalized. The primary s = 0.20 setting is accompanied by prespecified checks at s = 0.10 and 0.30; these magnitudes are modeling assumptions used only to examine whether conclusions depend on perturbation strength. We report Pr(1st), the share of draws in which a market ranks first; $Pr(baserank)$, the share retaining that market's baseline rank; and full-order retention, the share reproducing the complete five-country baseline sequence. Third,

leave-one-indicator-out (LOIO) analysis deletes one criterion, recomputes entropy weights over the remaining seven, and reruns TOPSIS. Fourth, a Spearman matrix on the direction-oriented frozen inputs is reported descriptively to expose criterion overlap. Fifth, preprocessing sensitivity repeats the full ranking procedure under the four transformation specifications defined above. No robustness diagnostic is used to retune the baseline weights or ranking.

4 Results

4.1 Entropy Weights and Baseline Ranking

The entropy weights in Fig. 2 are distributed across all eight indicators rather than collapsing onto one variable. GDP receives the largest weight at 17.73 percent, followed by secure servers at 15.16 percent, mobile subscriptions at 14.35 percent, inflation at 12.63 percent, and trade openness at 12.02 percent. GDP per capita, FDI, and Internet use receive 10.35, 9.25, and 8.50 percent, respectively. The relatively low Internet weight reflects limited cross-country dispersion in this five-market set, not an assumption that connectivity is unimportant.

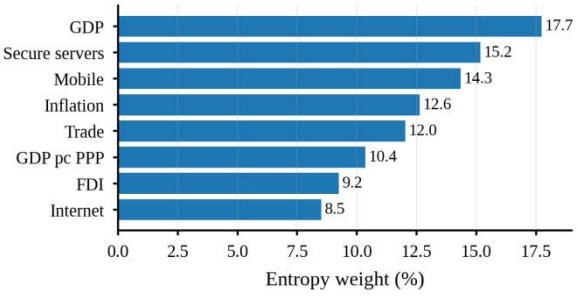


Fig. 2. Entropy-derived indicator weights from the frozen 2022-2024 decision matrix.

Table 3 reports the recomputed baseline ranking from the exact frozen matrix. The Russian Federation scores 0.6425 and ranks first, reflecting its exceptional market scale together with relatively strong purchasing power, mobile intensity, and secure-server density. Belarus ranks second at 0.5615, supported by high Internet use, trade openness, positive FDI inflows, and dense secure-server infrastructure. Kazakhstan ranks third at 0.4799, while Armenia and the Kyrgyz Republic form lower structural tiers under the baseline dispersion weights.

Table 3. Topsis scores and ranks

Market	Entropy	Rank	Equal	Rank
Russian Fed.	0.6425	1	0.5923	2
Belarus	0.5615	2	0.6233	1
Kazakhstan	0.4799	3	0.5201	3

Market	Entropy	Rank	Equal	Rank
Armenia	0.4444	4	0.4883	4
Kyrgyz Rep.	0.3241	5	0.3856	5

4.2 Robustness and Rank Uncertainty

Equal weighting changes the exact winner: Belarus moves to first with 0.6233 and the Russian Federation to second with 0.5923, while Kazakhstan, Armenia, and the Kyrgyz Republic retain third, fourth, and fifth. The reversal is analytically useful rather than inconvenient: entropy gives relatively greater combined influence to highly differentiating scale and infrastructure criteria, whereas equal weighting raises the aggregate contribution of criteria such as trade openness and FDI. The result therefore argues against presenting the baseline order as an invariant league table.

At the primary perturbation level s=0.20, the Russian Federation ranks first in 91.39 percent of draws and Belarus in 8.58 percent; Armenia accounts for 0.03 percent, while Kazakhstan and the Kyrgyz Republic never rank first. Full-order retention is 69.69 percent. Perturbation strength behaves monotonically as expected: at s=0.10 the Russian Federation is first in 99.67 percent of draws and full-order retention is 89.08 percent; at s=0.30 these values fall to 82.05 and 54.71 percent. Thus wider weight uncertainty weakens exact-rank stability without overturning the recurring Russian Federation-Belarus upper tier. Table 4 reports the primary s=0.20 country-level probabilities; the additional magnitudes are provided in Supplementary Table S1.

Table 4. Robustness summary

Market	Base	Equal	Pr(1st), %	Pr(base rank), %	Modal
Russian Fed.	1	2	91.39	91.39	1
Belarus	2	1	8.58	89.96	2
Kazakhstan	3	3	0.00	72.56	3
Armenia	4	4	0.03	73.87	4
Kyrgyz Rep.	5	5	0.00	99.74	5

Preprocessing sensitivity provides a complementary stability check. The baseline and GDP-only specifications retain the full Russian Federation–Belarus–Kazakhstan–Armenia–Kyrgyz Republic order, whereas the no-log and server-only specifications interchange Kazakhstan and Armenia. The Russian Federation and Belarus remain first and second, respectively, and the Kyrgyz Republic remains fifth under all four specifications. Supplementary Table S4 reports the complete rankings. Thus, the transformation choice affects the middle-tier ordering more than the recurring upper-tier pattern.

4.3 Single-Indicator Deletion Diagnostics

The leave-one-indicator-out results in Table 5 clarify where the ranking is structurally sensitive. GDP is the only omitted criterion that changes the winner: without GDP, Belarus moves to first and the Russian Federation to second. The third position is more conditional. Armenia moves ahead of Kazakhstan when GDP, Internet use, or secure-server intensity is removed, whereas Kazakhstan remains third under the other five deletions. The Kyrgyz Republic remains fifth in every deletion. The defensible conclusion is therefore a persistent upper pair and lowest tier, with a more criterion-dependent Kazakhstan-Armenia ordering.

Table 5. Leave-one-indicator-out ranking diagnostic

Omitted	1st	2nd	3rd
GDP	Belarus	Russian Fed.	Armenia
GDP pc PPP	Russian Fed.	Belarus	Kazakhstan
Internet	Russian Fed.	Belarus	Armenia
Mobile	Russian Fed.	Belarus	Kazakhstan
Secure servers	Russian Fed.	Belarus	Armenia
Trade	Russian Fed.	Belarus	Kazakhstan
FDI	Russian Fed.	Belarus	Kazakhstan
Inflation	Russian Fed.	Belarus	Kazakhstan

The correlation diagnostic complements LOIO rather than serving as an automatic deletion rule. Supplementary Table S2 reports Spearman correlations for the direction-oriented frozen inputs. GDP and PPP are perfectly rank-correlated ($\rho = 1.00$) in this five-country sample; both correlate strongly with secure-server intensity ($\rho = 0.90$) and inversely with trade openness ($\rho = -0.90$). Because $n = 5$ makes these coefficients descriptive rather than inferential, the study does not delete criteria post hoc. Instead, the correlations identify overlapping structural dimensions, while LOIO tests how the ranking responds to removal of each criterion. Only GDP removal changes the winner, indicating that GDP is the most visible single-criterion sensitivity in the current decision set. The correlation diagnostic does not remove potential redundancy; it makes that limitation explicit and separates it from the observed rank-stability results.

5 Discussion and Managerial Implications

5.1 Strategic Interpretation of the Market Tiers

Two findings are more defensible than a simple league table. First, the Russian Federation and Belarus form a persistent upper tier. The Kyrgyz Republic remains fifth under every LOIO deletion and retains its baseline fifth position in 99.74% of the primary $s = 0.20$ perturbation draws. The preprocessing sensitivity analysis likewise preserves the Russian Federation–Belarus upper pair and the Kyrgyz Republic's fifth position across all four specifications, although the Kazakhstan–Armenia ordering

changes under some transformations. Kazakhstan therefore generally occupies an intermediate position, but its exact ordering relative to Armenia is more assumption-sensitive. Second, the ranking reflects distinct market profiles rather than universal dominance. The Russian Federation combines exceptional scale and digital-server capacity but relatively low trade openness and negative FDI inflow in the period; Belarus combines openness and digital infrastructure with smaller scale; Kazakhstan has strong purchasing power and Internet use; Armenia is comparatively open but smaller; and the Kyrgyz Republic is trade-intensive but constrained by scale and secure-server depth. The index should therefore be read as a structured screening profile rather than a league table of guaranteed commercial performance.

The result also demonstrates why market attractiveness should be interpreted as a profile rather than a single score. The Russian Federation does not dominate every criterion: its low trade-to-GDP ratio and negative average FDI inflow are material counter-signals. Belarus, by contrast, combines much smaller absolute market scale with relatively strong openness and digital infrastructure. Kazakhstan has a stronger demand profile than Armenia but is penalized by macroeconomic instability over the study window. These trade-offs are exactly the type of information that is lost when managers rely on market size or Internet penetration alone.

5.2 How Chinese Firms Should Use the Ranking

For Chinese firms, the index is best used as the structural host-market layer of staged market screening. The EEC has treated China as an important counterpart in cross-border e-commerce development [9], but the composite score itself is not a measure of bilateral advantage. Its role is to prioritize EAEU markets for deeper China-specific analysis of product demand, tariffs and certification, platform access, localization costs, last-mile logistics, payments, settlement, compliance, and partner quality. This use is consistent with international-business research that treats entry decisions as contingent on institutional and transaction-cost conditions rather than as a single national score [14]–[16].

Weight sensitivity is strategically meaningful. A scale-seeking firm may emphasize GDP, purchasing power, and digital infrastructure and therefore favor a market profile similar to the baseline. A niche exporter facing compliance or logistics constraints may place greater weight on openness or operational accessibility. The equal-weight reversal between the Russian Federation and Belarus is therefore not a defect to conceal; it shows why decision makers should inspect assumptions before treating a small score gap as a categorical recommendation.

The scores are relative to the five EAEU alternatives: a value such as 0.64 is a TOPSIS closeness coefficient within this decision set, not '64 percent attractive' and not a market-success probability. The model should therefore be used for comparative screening, not for absolute forecasting.

5.3 Limitations and Scope Conditions

Several limitations constrain interpretation. First, the candidate set contains only five EAEU members, so entropy weights are endogenous to this decision universe and may change if non-EAEU markets are added. Second, the three-year mean improves temporal stability but does not capture within-period shocks or structural breaks. Third, the index intentionally represents structural host-market conditions; it does not include bilateral tariffs, sanctions/export controls, platform-specific access, product demand, logistics costs, payments, or firm capabilities. These should enter second-stage due diligence rather than being inferred from the composite score.

Fourth, the model estimates no causal effect of digital readiness or openness on firm performance; the ranks are not expected sales, profits, or survival probabilities. Fifth, public indicators may be revised by source agencies. Reproducibility is protected by treating Table 2 and Supplementary Data S1 as the frozen computational matrix and by releasing the complete script and analysis settings. Finally, the 50,000-draw perturbation analysis tests weight uncertainty rather than forecasting uncertainty; its three magnitudes should be interpreted as stress scenarios, not estimated probabilities of managerial preference.

Some criteria are correlated because scale, purchasing power, digital infrastructure, and openness can co-move across a small country set. The revised Spearman diagnostic makes that overlap explicit, while LOIO tests whether any single criterion is indispensable to the observed ranking. These checks do not make Entropy-TOPSIS correlation-adjusted; they delimit the claim more precisely. A future extension could compare a correlation-aware or firm-elicited weighting scheme on a larger candidate set when suitable bilateral and product-level data are available.

6 Conclusion

This study develops a transparent Entropy–TOPSIS screening design for structural CBEC market attractiveness across the five EAEU members from a Chinese-firm decision perspective. Using an exact frozen 2022–2024 public-data matrix, the baseline ranks the Russian Federation, Belarus, Kazakhstan, Armenia, and the Kyrgyz Republic in descending order. Equal weighting reverses the top pair. Weight perturbation shows a recurrent Russian Federation–Belarus upper tier, while preprocessing sensitivity preserves the upper pair and fifth-ranked market but qualifies the Kazakhstan–Armenia ordering. LOIO identifies GDP as the most visible single-criterion sensitivity, and the correlation diagnostic exposes overlap among several structural dimensions. The contribution is a reproducible country-level decision-support design with explicit construct boundaries and rank-stability diagnostics. For Chinese firms, the resulting score is suitable for first-stage structural screening and should be followed by bilateral, product-level, logistics, payment, compliance, and firm-specific due diligence.

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Supplementary Tables S1–S4

For: Evaluating Structural Cross-Border E-Commerce Market Attractiveness in the Eurasian Economic Union for Chinese Firms: An Entropy–TOPSIS Analysis Using Multi-Source Public Data

This document displays the supplementary tables cited in the manuscript. The corresponding machine-readable CSV files and reproduction scripts are included in the accompanying supplementary ZIP package.

Supplementary Table S1. Monte Carlo weight-perturbation magnitude sensitivity

50,000 independent weight-perturbation draws at each σ ∈ {0.10, 0.20, 0.30}; fixed random seed = 20260810. All probability columns are proportions (0–1); 0.91390 corresponds to 91.39%. "Full-order retention" is constant across markets within a given σ.

σ	Market	Pr(1st)	Pr(base rank)	Mean rank	Full-order retention
0.10	Russian Federation	0.99674	0.99674	1.00326	0.89082
0.10	Belarus	0.00326	0.99674	1.99674	0.89082
0.10	Kazakhstan	0.00000	0.89184	3.10816	0.89082
0.10	Armenia	0.00000	0.89184	3.89184	0.89082
0.10	Kyrgyz Republic	0.00000	1.00000	5.00000	0.89082
0.20	Russian Federation	0.91390	0.91390	1.08908	0.69694
0.20	Belarus	0.08578	0.89964	1.92880	0.69694
0.20	Kazakhstan	0.00000	0.72556	3.25070	0.69694
0.20	Armenia	0.00032	0.73866	3.73410	0.69694
0.20	Kyrgyz Republic	0.00000	0.99736	4.99732	0.69694
0.30	Russian Federation	0.82052	0.82052	1.21856	0.54710
0.30	Belarus	0.17300	0.74588	1.90814	0.54710
0.30	Kazakhstan	0.00000	0.60826	3.28576	0.54710
0.30	Armenia	0.00648	0.66964	3.61860	0.54710
0.30	Kyrgyz Republic	0.00000	0.97198	4.96894	0.54710

Pr(1st) is the frequency of being ranked first; Pr(base rank) is the frequency of retaining the original baseline rank. Mean rank is the Monte Carlo average.

Supplementary Table S2. Spearman correlation matrix of direction-oriented indicators

Spearman rank correlations are calculated on the five-country frozen 2022–2024 aggregate matrix after directing inflation as a cost criterion. These correlations are descriptive only (n = 5); they are not hypothesis-test results or an automatic variable-selection rule.

Indicator	GDP	PPP	Internet	Mobile	Servers	Trade	FDI	Inflation
GDP	1.00	1.00	0.80	0.60	0.90	-0.90	-0.40	-0.20
PPP	1.00	1.00	0.80	0.60	0.90	-0.90	-0.40	-0.20
Internet	0.80	0.80	1.00	0.00	0.60	-0.60	-0.50	-0.70
Mobile	0.60	0.60	0.00	1.00	0.70	-0.70	0.00	0.60
Servers	0.90	0.90	0.60	0.70	1.00	-0.70	-0.30	0.10
Trade	-0.90	-0.90	-0.60	-0.70	-0.70	1.00	0.30	0.10
FDI	-0.40	-0.40	-0.50	0.00	-0.30	0.30	1.00	0.60
Inflation	-0.20	-0.20	-0.70	0.60	0.10	0.10	0.60	1.00

GDP and PPP have ρ = 1.00. Both correlate with secure-server intensity (ρ = 0.90) and trade openness (ρ = −0.90).

Supplementary Table S3. Leave-one-indicator-out rankings

For each row, the omitted criterion is excluded, entropy weights are recomputed for the remaining seven criteria, and TOPSIS is rerun. All five rank positions are shown.

Omitted criterion	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
GDP	Belarus	Russian Federation	Armenia	Kazakhstan	Kyrgyz Republic
PPP	Russian Federation	Belarus	Kazakhstan	Armenia	Kyrgyz Republic
Internet	Russian Federation	Belarus	Armenia	Kazakhstan	Kyrgyz Republic
Mobile	Russian Federation	Belarus	Kazakhstan	Armenia	Kyrgyz Republic
Servers	Russian Federation	Belarus	Armenia	Kazakhstan	Kyrgyz Republic
Trade	Russian Federation	Belarus	Kazakhstan	Armenia	Kyrgyz Republic
FDI	Russian Federation	Belarus	Kazakhstan	Armenia	Kyrgyz Republic
Inflation	Russian Federation	Belarus	Kazakhstan	Armenia	Kyrgyz Republic

This is the full five-rank version of the first-to-third-rank summary reported as Table 5 in the manuscript.

Supplementary Table S4. Preprocessing sensitivity

Each preprocessing specification is evaluated through the entire Entropy–TOPSIS workflow, with no tuning to the baseline outcome.

Specification	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
Baseline: log GDP + Servers	Russian Federation	Belarus	Kazakhstan	Armenia	Kyrgyz Republic
No log transformation	Russian Federation	Belarus	Armenia	Kazakhstan	Kyrgyz Republic
Log GDP only	Russian Federation	Belarus	Kazakhstan	Armenia	Kyrgyz Republic
Log Servers only	Russian Federation	Belarus	Armenia	Kazakhstan	Kyrgyz Republic

GDP and secure Internet servers are the two criteria subject to the ln(1 + x) preprocessing option.

16.

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