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Econometric Screening and Robust MCDM for Regional Small-Business Support Decisions: Evidence from Uzbekistan

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ABSTRACT

Objective: This study develops an empirically screened decision-support framework for regional small-business support. It asks how econometric evidence can restrict the admissible criterion set without turning conditional associations into policy preferences, and whether regional need priorities remain stable under alternative modelling choices.

Methods: Two-way fixed-effects models are estimated for 14 regions of Uzbekistan: real net-sales intensity for 2013–2022 (N=140) and small-business exports for 2013–2024 (N=168), with 9,999-repetition wild cluster bootstrap-t inference. Capital-intensity shortfall, overdue-payables burden and graduate-flow shortfall form a need matrix under explicit policy-orientation assumptions; small and medium-sized enterprise (SME) employment is reported separately as implementation scale. Robustness covers 54 structural specifications, all criterion subsets, opposing net-entry interpretations, rolling three-year windows and Dirichlet weight perturbations.

Results: Capital intensity (β=0.2249; wild p=0.0016), overdue-payables pressure (β=−0.0675; p=0.0376), graduate-flow intensity (β=0.9704; p=0.0108) and SME employment scale (β=2.6171; p=0.0246) pass the primary screen. Under two-way region–year clustering, only overdue payables weakens (p=0.071) and is treated as a provisional need signal. Andijan, Kashkadarya and Fergana rank highest; Andijan ranks first in all 54 structural variants, and the top-three set is preserved in 53. Under unrestricted weight uncertainty, top-three probabilities are 0.993 for Andijan, 0.795 for Fergana and 0.734 for Kashkadarya. Rolling windows show substantial temporal variation.

Conclusion: The framework supports auditable regional need prioritization, not welfare-optimal funding shares or causal treatment claims. Econometric relevance, policy orientation, information weighting and implementation scale should be kept analytically distinct and updated as the data window changes.

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1. Introduction

Regional business-support programmes face a problem that is partly econometric and partly operational. A ministry may observe many regional indicators, but only some are empirically connected to the performance dimensions that the programme is meant to improve. Even after those indicators are screened, a second problem remains: a statistical association does not tell the decision maker whether a low or high regional value should be treated as a priority, how competing criteria should be weighted, or whether a ranking is stable enough to guide managerial attention. Treating those questions as if they were solved by one regression coefficient or one MCDM score creates an avoidable chain of hidden assumptions.

The distinction matters in Uzbekistan. Small-business conditions differ markedly across the country's 14 first-level regions, while public programmes operate under a national policy architecture. Regions vary in productive capital, payment pressure, skills supply, export activity and the scale of the small and medium-sized enterprise (SME) employment base. A uniform support rule can therefore miss territorially concentrated constraints. At the same time, a ranking built mechanically from regional disparities can also mislead: a variable may vary strongly across regions without being relevant to small-business performance, and a criterion may be empirically relevant without possessing an unambiguous policy direction. The World Bank's recent Country Economic Memorandum documents opaque selection criteria and evidence of mis-targeting in Uzbekistan's business-support measures during 2020–2022, underscoring the value of a transparent and auditable prioritization process (World Bank, 2025).

Multi-Criteria Decision-Making (MCDM) is well suited to transparent comparison of heterogeneous regional conditions, but methodological transparency requires more than selecting a familiar ranking operator. Three separations are essential. First, empirical admissibility is distinct from policy orientation. Fixed-effects estimates can establish a conditional within-region association; they cannot by themselves establish that low values constitute need or that public spending would reverse the association. Second, information weighting is distinct from policy importance. Entropy and CRITIC (CRiteria Importance Through Intercriteria Correlation) describe how much a criterion discriminates among alternatives; they do not estimate social welfare weights. Third, need is distinct from implementation scale. A region may face severe constraints but have a small beneficiary base, while another may have a large SME employment base but comparatively limited need. Allowing the latter to compensate for the former in one score obscures the decision problem.

The framework is built around these distinctions. The econometric stage screens candidate variables using two-way fixed effects, few-cluster robust inference, leave-one-region-out stability and targeted robustness checks. A separate decision-design stage then states the policy orientation of the admitted variables explicitly. Three deficit or burden signals—capital-intensity shortfall, overdue-payables burden and graduate-flow shortfall—form the need matrix. SME employment is retained only as an implementation-scale indicator and is reported alongside, rather than inside, the need score. The MCDM stage then tests whether need rankings survive alternative normalization rules, weights, aggregation operators, criterion sets and stochastic weight distributions.

The common policy objective that links the two econometric blocks is deliberately limited: to identify regional constraints associated with two complementary dimensions of small-business competitiveness—intensive domestic performance and external-market participation—and then to organize those constraints into an auditable need-prioritization exercise. The objective is not to estimate the causal return to a grant, loan or training programme. Domestic sales intensity and exports therefore serve as screening outcomes, not as components of a single welfare function. This narrower objective provides the bridge between the econometric evidence and the decision layer while preserving the limits of the data.

Three research questions follow. RQ1 asks which candidate regional variables display sufficiently stable conditional associations with the two small-business performance outcomes to remain empirically admissible. RQ2 asks whether the resulting need ranking is robust to alternative normalization, weighting, aggregation and criterion-set assumptions when implementation scale is kept separate. RQ3 asks how strongly the ranking depends on the weight space and on

the choice of the decision window. The answers are intended to support a repeatable decision process rather than a fixed funding formula.

The contribution is therefore not another MCDM operator. Hybrid econometric–MCDM designs already exist, including recent regional work that combines panel regression with fuzzy MCDM (Profiroiu et al., 2025). The distinctive feature here is the governance of the analytical sequence: candidate criteria first face an econometric admissibility gate; policy orientation is then declared as a normative design choice rather than inferred from coefficients; information weights are prevented from masquerading as policy weights; need and implementation scale are separated; and robustness is evaluated over model structure, criterion composition, unrestricted weights and time windows. This architecture responds to the practical question of how much confidence a decision maker should place in a regional priority band when each modelling layer contains uncertainty.

2. Literature Review

2.1 MCDM, objective weighting and robustness

MCDM methods provide formal rules for comparing alternatives described by criteria expressed in different units. The Weighted Sum Model (WSM) is fully compensatory, the Weighted Product Model (WPM) penalizes profiles with very weak dimensions, and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) ranks alternatives by relative proximity to an ideal profile (Hwang & Yoon, 1981; Triantaphyllou, 2000). Method choice is consequential because normalization, compensation and distance geometry can alter rankings even when the underlying decision matrix is unchanged (Behzadian et al., 2012; Opricovic & Tzeng, 2004). Consequently, agreement across methods is evidence about stability, not a reason to treat any one operator as intrinsically correct.

Weighting introduces a separate source of uncertainty. Shannon entropy gives more weight to criteria with greater discriminatory information in the observed matrix, while CRITIC combines dispersion with conflict among criteria (Diakoulaki et al., 1995; Shannon, 1948). Neither method reveals a social preference function. An entropy weight can be large because a criterion separates regions sharply; that fact does not show that policymakers value the criterion more highly or that its causal return is larger. Equal weighting is therefore useful as a neutral benchmark, while preference-sensitive results require explicit policy elicitation rather than statistical re-labelling.

Sensitivity analysis has become central to credible multi-criteria decision analysis (MCDA) because rankings can change with weights, normalization and the criterion set. Stochastic multicriteria acceptability analysis (SMAA) treats the weight vector as uncertain and reports rank acceptability (Lahdelma & Salminen, 2001). The systematic review by Więckowski and Sałabun (2023) documents substantial variation in sensitivity practice and argues for analysis that exposes how modelling choices affect rankings. Their later COMSAM framework expands sensitivity across multiple parameters (Więckowski & Sałabun, 2024). Lotfi et al. (2023) similarly integrate robustness, resilience and risk in an MCDM location problem, while O'Shea et al. (2026) formalize weight-stability intervals for WSM. Related applications in the journal ecosystem also show why weighting and sensitivity must be made visible: Patil et al. (2020) combine Fuzzy TOPSIS and Grey Relational Analysis for supplier selection and perturb preferential weights, Moradi and Moradi (2021) integrate the analytic hierarchy process (AHP) and TOPSIS for performance evaluation, and Neisi et al. (2025) use the fuzzy analytic network process (ANP) to rank integrated supply-chain performance factors. These studies reinforce the value of explicit robustness checks, while the present framework adds an econometric admissibility layer before MCDM.

2.2 Hybrid econometric–MCDM designs and the remaining design problem

The closest literature shows that econometrics and MCDM need not be separate exercises. Muneeb et al. (2025) use an integrated MCDM approach to identify critical success factors for SMEs in emerging markets, while Rodríguez-Carrillo et al. (2025) document substantial heterogeneity in criteria, weighting and validation practices across SME-focused MCDM applications. Profiroiu et al. (2025) combine fuzzy TOPSIS and ELECTRE with panel regression and Granger-causality analysis to assess regional economic performance in Romania. These studies establish the feasibility

of hybrid empirical–decision frameworks. They also make an important comparison point for the present design: the novelty cannot be claimed simply from placing a regression and an MCDM model in the same paper.

The unresolved issue is how the outputs of the empirical model acquire a role in the decision model. A regression can establish relevance to an outcome, but the mapping from a coefficient to a benefit-type or cost-type criterion is a separate policy judgement. Likewise, objective weighting can quantify information dispersion, but it does not determine normative importance. If these stages are collapsed, the same data variation can appear first as statistical evidence and again as a large entropy weight, creating the impression of stronger policy support than either stage provides on its own. The architecture developed below makes each transition observable and independently contestable.

Table 1. Positioning against the closest methodological studies

Study	Decision setting	Empirical/econometric layer	MCDM/robustness layer	Distinction relevant to this study
Muneeb et al. (2025)	SME critical-success factors; integrated MCDM	No panel-econometric admission gate reported	Integrated weighting/ranking	No explicit separation of statistical admissibility, policy orientation and information weighting
Profiroiu et al. (2025)	Romanian regional performance	Panel regression and Granger analysis	Fuzzy TOPSIS and ELECTRE	Hybrid regional design; differs from the present pre-MCDM admissibility gate and need/implementation separation
Lotfi et al. (2023)	Renewable-energy location under risk	No econometric screening of criteria	Robust/resilience MCDM with risk	Demonstrates robustness under uncertainty; present study adds empirical admission and temporal/criterion-set sensitivity
Więckowski & Sałabun (2024)	General MCDA sensitivity	Not an empirical screening study	Multi-parameter COMSAM sensitivity	Provides sensitivity logic; present application adds econometric screening and regional SME decision design
Present study	Regional SME support decisions	Two FE screens; wild-cluster inference; admission gates	Need-only MCDM + separate implementation scale	Separates empirical relevance, normative orientation, information weighting, criterion-set uncertainty and decision-window uncertainty

2.3 Regional SME constraints, skills supply and implementation scale

The substantive variables also require different interpretations. Access to productive capital and financial stress are established constraints on SME performance (Beck & Demirgüç-Kunt, 2006). A positive association between capital intensity and sales intensity is consistent with productive-capital constraints, while a negative association between overdue payables and performance is consistent with liquidity or payment stress. Neither relationship proves that a particular credit instrument would generate the estimated gain; the coefficient is an admissibility signal, not a treatment effect.

The education proxy used here is the annual number of university graduates per 1,000 working-age residents. It is therefore more accurately described as graduate-flow intensity than as a stock of human capital. The variable can proxy the regional flow of tertiary-educated skills potentially available to exporting firms, but it does not measure accumulated worker skills, managerial quality or firm-specific absorptive capacity. Renaming the variable is consequential because the decision layer reverses it into a graduate-flow shortfall; the interpretation must match what the data actually measure.

SME employment is different again. A large employment base may indicate economic strength rather than deprivation. It can also imply that a programme has a larger potential beneficiary base and greater operating scale. For this reason, SME employment is not included as a need criterion. It is presented as an implementation-scale descriptor.

This follows the broader principle that a scale or capacity measure should not automatically offset a deficit measure in a compensatory index. The distinction is consistent with evidence that the effectiveness of firm support can vary with regional conditions, so territorial context should inform programme design without being mistaken for an estimated treatment return (Mulligan, 2024).

The regional targeting problem is also directly relevant to Uzbekistan's recent policy experience. The World Bank (2025) reports that many business-support measures introduced during 2020–2022 lacked transparent selection and budget-allocation information and documents evidence of mis-targeting across firms and sectors. That evidence does not validate the criteria used in this study, but it strengthens the case for a decision process in which admission rules, criterion orientation and ranking uncertainty can be inspected separately.

3. Materials and Methods

3.1 Data, estimation samples and measurement scope

The analysis covers the 14 first-level regions of Uzbekistan. The domestic-performance panel spans 2013–2022 (140 region-year observations) and the export panel spans 2013–2024 (168 observations). The regional series are drawn from the National Statistics Committee's Statistical Information and Analytical System (SIAT; National Statistics Committee of the Republic of Uzbekistan, n.d.). The supplementary workbook reports the SIAT series identifiers, variable transformations and the frozen estimation data used for every reported result.

The domestic outcome is the logarithm of real net-sales intensity relative to the official SIAT count of active small enterprises and microfirms. The numerator is the SIAT series for net sales of small enterprises and microfirms; the denominator is the average of the active small-enterprise and microfirm counts recorded at the beginning of year t and the beginning of year t+1. These are separate official series and their statistical populations are related but not guaranteed to be identical. The outcome is therefore interpreted as a regional sales-intensity proxy, not as literal average revenue for a strictly identical population of firms. Denominator-safe robustness checks re-estimate the domestic relationship using total real sales with the active-entity scale entered separately.

Capital intensity is real fixed assets divided by the same active-entity scale, lagged one year and logged. Financial pressure is overdue payables relative to total payables, transformed as ln(1+x) and lagged. Net entry is retained in the domestic regression as a control. In the export model, the outcome is ln(1+small-business exports). Graduate-flow intensity is university graduates per 1,000 working-age residents, transformed as ln(1+x) and lagged. SME employment is measured in thousands, logged and lagged. The graduate-flow label is used because the variable measures an annual tertiary-graduate flow rather than a stock of human capital.

The baseline decision matrix is built from the lagged criterion columns recorded in model rows 2020–2022. Because the econometric predictors enter at t−1, these rows represent underlying criterion states from 2019–2021. This timing is reported explicitly to distinguish estimation years from the decision-state years. The window is historical rather than a claim about current 2026 needs. Rolling-window sensitivity evaluates how the ranking changes when the three-year decision state is shifted backward through the panel.

3.2 Common policy objective and separation of analytical roles

The two econometric outcomes are combined only at the level of the policy question, not through a common regression coefficient. The decision objective is to prioritize regional constraints associated with two complementary dimensions of small-business competitiveness: intensive domestic performance and external-market participation. The domestic model screens capital and financial-stress candidates; the export model screens skills-supply and employment-scale candidates. The subsequent orientation of a screened variable is not identified by its coefficient. It is a declared decision-design assumption.

Four analytical roles are therefore kept separate. Empirical relevance asks whether a candidate has a stable conditional association with a performance outcome. Policy orientation asks whether a high or low regional value should be treated as a deficit or burden under a stated support objective. Information weighting asks how strongly a

criterion differentiates regions in the selected decision window. Implementation scale describes the potential size of the beneficiary base. Only the first role is econometric; the second is normative; the third is data-discriminatory; and the fourth is contextual.

Table 2. Measurement, analytical role and interpretation

Variable	Construction	Analytical role	Sample	Interpretive boundary
Domestic sales-intensity proxy	Real net sales of small enterprises and microfirms / average number of active small enterprises and microfirms	Outcome	2013–2022	Sales-intensity proxy; numerator and active-entity denominator are separate official series with related but not guaranteed-identical statistical populations
Capital intensity	Real fixed assets / active scale; ln; t−1	Screening variable → need orientation	2013–2022	Low value is treated as shortfall only under an explicit constraint-relief policy assumption
Overdue-payables pressure	Overdue / total payables; ln(1+x); t−1	Screening variable → need orientation	2013–2022	High value treated as financial-stress burden
Net entry	Net entry rate; t−1	Control; sensitivity only	2013–2022	Excluded from core decision model because policy direction is ambiguous
SME exports	ln(1+exports)	Outcome	2013–2024	External-market participation scale
Graduate-flow intensity	University graduates / 1,000 working-age; ln(1+x); t−1	Screening variable → need orientation	2013–2024	Graduate-flow proxy, not human-capital stock; low value treated as skills-supply shortfall under the stated policy orientation
SME employment scale	ln(employment); t−1	Implementation-scale context	2013–2024	Potential beneficiary-base/operating scale; reported separately and never allowed to compensate for need

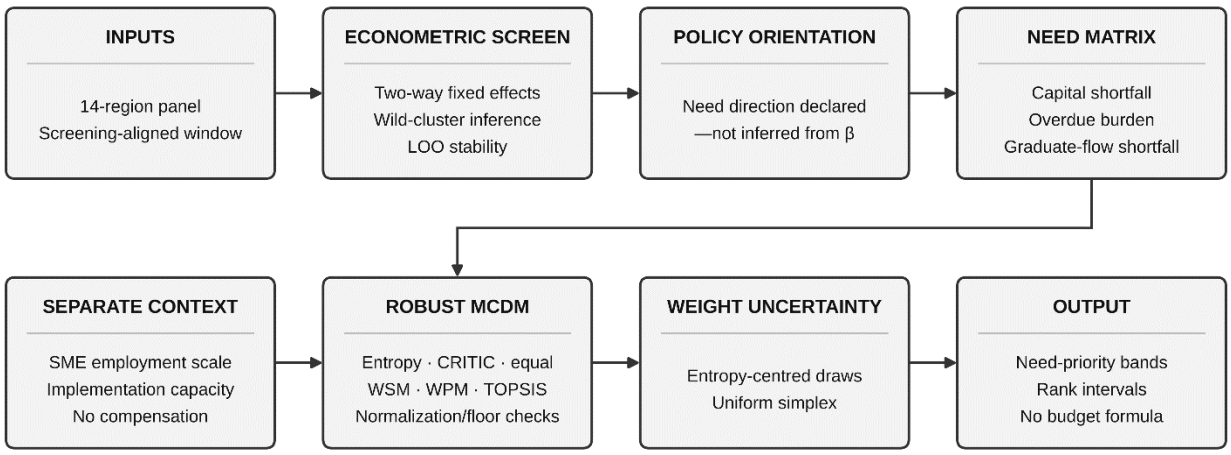


Figure 1. Evidence-screened decision-support architecture.

3.3 Econometric screening and primary inference

$$y_{it}^{D} = \beta_1 x_{1,i,t-1} + \beta_2 x_{2,i,t-1} + \beta_3 x_{3,i,t-1} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (1)$$

$$y_{it}^{X} = \gamma_1 z_{1,i,t-1} + \gamma_2 z_{2,i,t-1} + \alpha_i + \lambda_t + u_{it} \quad (2)$$

Equation (1) models log real sales intensity using lagged capital intensity, overdue-payables pressure and net entry; Equation (2) models ln(1+exports) using lagged graduate-flow intensity and SME employment. Region fixed effects absorb time-invariant territorial heterogeneity and year effects absorb common shocks. The coefficients are conditional within-region associations and are not interpreted as structural treatment effects.

Estimator choice is supported by panel diagnostics. Breusch–Pagan LM tests reject pooled representations, Mundlak (1978) diagnostics reject random-effects exogeneity, and the residual structure exhibits groupwise heteroskedasticity, serial correlation and cross-sectional dependence. With only 14 region clusters, conventional cluster-robust asymptotics are unreliable. Primary screening therefore uses null-imposed wild cluster bootstrap-t tests by region with 9,999 Rademacher replications (Cameron et al., 2008; MacKinnon & Webb, 2017). Clustered standard errors remain descriptive. Because one-way clustering by region does not itself accommodate contemporaneous dependence across regions, an additional robustness layer uses two-way region–year cluster-robust covariance estimates. The two-way covariance follows the Cameron–Gelbach–Miller inclusion–exclusion construction with finite-sample corrections; p-values are referenced to a t distribution with degrees of freedom equal to the smaller cluster dimension minus one (9 for the domestic panel and 11 for the export panel). Driscoll–Kraay estimates (Driscoll & Kraay, 1998) remain a secondary sensitivity check because the short time dimension limits their standalone evidentiary value.

The first-difference robustness regressions include year effects and are evaluated with the same few-cluster logic: 9,999 null-imposed Rademacher wild cluster bootstrap-t draws clustered by region. Conventional region-clustered p-values are retained only as descriptive comparators. For the primary level models, Stata 15.1 boottest is run after xtreg, fe vce(cluster region_id) using commands of the form boottest variable, cluster(region_id) reps(9999) seed(#) nograph. The default null-imposed Rademacher bootstrap and symmetric two-sided p-value convention [ptype(symmetric)] are retained. The reported 95% confidence sets are obtained by inversion of those same restricted bootstrap-t tests at level(95); no nonull, noci or alternative ptype() option is used. Variable-specific seeds are reported in the supplementary workbook.

A candidate passes the primary empirical gate when the region-cluster wild-bootstrap test supports the coefficient at the 5% level, the sign remains unchanged in all 14 leave-one-region-out estimates, and the variable has a defensible operational interpretation. The two-way region–year sensitivity qualifies that decision rather than redefining the gate ex post. If a coefficient weakens under the dependence-robust check, it is labelled provisional and the decision model must show how rankings change when that criterion is removed. Wild-bootstrap confidence intervals are reported alongside the primary p-values in the results table.

3.4 From empirical admissibility to policy orientation

Passing the econometric screen is necessary but not sufficient for entry into the need matrix. Capital intensity is reversed only because the decision problem adopts a constraint-relief objective: conditional on the screening evidence, lower productive-capital intensity is treated as a larger capital shortfall. This is a normative mapping, not a result identified by β_1. Overdue-payables pressure is oriented directly because higher arrears represent greater financial stress. Graduate-flow intensity is reversed because lower annual tertiary-graduate supply is treated as a skills-supply shortfall relevant to external-market capability. SME employment is not reversed or included in the need score; it is shown separately as implementation scale.

Net entry illustrates why the orientation gate matters. Its regression coefficient is statistically stable, but high entry can signal entrepreneurial dynamism, excessive churn, fragmentation or registry effects. There is no unambiguous monotonic policy direction. Instead of converting the coefficient into a criterion, the sensitivity analysis deliberately

adds net entry twice—once treating high entry as a burden and once treating low entry as a deficit—to show how strongly this unresolved normative choice would affect rankings.

3.5 Need matrix, weighting and aggregation

$$g_{ij} = \frac{q_j^{\max} - q_{ij}}{q_j^{\max} - q_j^{\min}}, \quad \text{shortfall criterion}$$
$$g_{ij} = \frac{q_{ij} - q_j^{\min}}{q_j^{\max} - q_j^{\min}}, \quad \text{burden criterion} \tag{3}$$

The baseline need matrix contains three continuous columns: capital-intensity shortfall, overdue-payables burden and graduate-flow shortfall. Min–max orientation maps each column to [0,1], with larger values denoting greater need. For robustness, vector-distance normalization divides each oriented column by its Euclidean norm, whereas rank-percentile normalization maps regional order positions to [0,1]. These transformations preserve criterion direction but change relative spacing; entropy and CRITIC weights are recalculated within every normalized matrix.

Entropy, CRITIC and equal weights are evaluated separately. Entropy measures cross-regional information dispersion, CRITIC combines dispersion with inter-criterion conflict, and equal weights impose no data-driven differentiation. These weights are never interpreted as policy importance or causal effect size.

$$p_{ij} = \frac{g_{ij}}{\sum_{i=1}^{n} g_{ij}}, \quad e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} p_{ij} \ln p_{ij}, \quad d_j = 1 - e_j, \quad w_j^E = \frac{d_j}{\sum_{k=1}^{m} d_k} \tag{4}$$

$$c_j = \sigma_j \sum_{k=1}^{m} \left(1 - \rho_{jk}\right), \quad w_j^C = \frac{c_j}{\sum_{k=1}^{m} c_k} \tag{5}$$

$$S_i^{WSM} = \sum_{j=1}^{m} w_j \, g_{ij} \tag{6}$$

$$r_{ij} = f + (1 - f) g_{ij}, \quad S_i^{WPM} = \prod_{j=1}^{m} r_{ij}^{w_j}, \quad 0 < f < 1 \tag{7}$$

$$z_{ij} = \frac{g_{ij}}{\sqrt{\sum_{i=1}^{n} g_{ij}^2}} \tag{8a}$$

$$v_{ij} = w_j z_{ij} \tag{8b}$$

$$v_j^P = \max_i v_{ij}, \qquad v_j^N = \min_i v_{ij} \tag{8c}$$

$$D_i^P = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^P\right)^2}, \qquad D_i^N = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^N\right)^2} \tag{8d}$$

$$C_i = \frac{D_i^N}{D_i^P + D_i^N} \tag{8e}$$

WSM is additive and fully compensatory. WPM is multiplicative and uses a strictly positive floor f; the analysis varies f over 0.01, 0.05, 0.10 and 0.20 rather than treating a single floor as fixed. Equations (8a–e) define TOPSIS: z is vector-normalized need, v is weighted normalized need, the P- and N-designated v terms denote the positive and negative ideal profiles, and the corresponding D terms are their Euclidean distances, and C is relative closeness to the positive ideal. No MCDM score is converted into a budget share. A funding formula would require explicit welfare weights, programme costs, minimum-service constraints, equity rules and evidence on causal returns that are outside the present data.

3.6 Robustness and uncertainty design

The robustness design addresses five sources of decision-model uncertainty. First, the three normalization rules are crossed with entropy, CRITIC and equal weights and with WSM, WPM and TOPSIS; the four WPM floors generate 54 distinct structural variants. Second, all non-empty subsets of the three need criteria are evaluated to reveal whether weaker econometric evidence materially changes the priority set. Third, the two opposing net-entry orientations show whether its exclusion is consequential. Fourth, rolling three-year windows from model rows 2013–2015 through 2020–2022 test temporal stability; their underlying lagged criterion years are reported explicitly. Fifth, weight uncertainty is examined both locally and globally.

Local weight uncertainty uses Dirichlet distributions centred on the entropy vector with concentration parameters 20, 50 and 100. To avoid interpreting stability around entropy as stability across the whole preference space, the analysis also draws 10,000 weights from Dirichlet(1,1,1), which is uniform over the three-criterion simplex. The resulting top-three probabilities and rank intervals describe preference sensitivity rather than statistical confidence intervals.

$$w^{(b)} \sim \text{Dirichlet}(\kappa w^{E}) \quad \text{and} \quad w^{(b)} \sim \text{Dirichlet}(1,1,1), \quad b = 1, \dots, B \tag{9}$$

$$P_i(\text{top } K) = \frac{1}{B}\sum_{b=1}^{B} \mathbf{1}\{R_i^{(b)} \le K\}, \quad \overline{R}_i = \frac{1}{B}\sum_{b=1}^{B} R_i^{(b)} \tag{10}$$

3.7 Reproducibility

The supplementary package contains the frozen M1 and M2 estimation datasets, source documentation, the need matrix, all 54 structural variants, all seven criterion subsets, net-entry orientation tests, rolling-window rankings, unrestricted and entropy-centred weight simulations, wild-bootstrap confidence intervals, the two-way region–year dependence check, and few-cluster first-difference inference. It also records the boottest seeds, tail convention and test-inversion procedure used for the primary confidence sets. No individual-level or confidential information is used.

4. Results

4.1 Econometric screen and evidentiary strength

The diagnostics confirm the need for few-cluster robust inference. In the domestic model, the Breusch–Pagan LM statistic is 211.45 ($p<0.001$) and the Mundlak test rejects random-effects exogeneity ($p=0.0005$). In the export model, the corresponding figures are 516.23 ($p<0.001$) and $p=0.0199$. Modified Wald and Wooldridge (2010) tests detect heteroskedasticity and serial correlation, while Pesaran CD tests reject cross-sectional independence in both models. These features are treated as characteristics of the panel rather than as problems claimed to be eliminated.

All four substantive candidates pass the primary region-cluster wild-bootstrap screen. Capital intensity is positively associated with domestic sales intensity ($\beta=0.2249$; wild $p=0.0016$), while overdue-payables pressure is negative ($\beta=-0.0675$; $p=0.0376$). Graduate-flow intensity is positively associated with exports ($\beta=0.9704$; $p=0.0108$), as is SME employment scale ($\beta=2.6171$; $p=0.0246$). All four signs survive every leave-one-region-out re-estimation. Table 3 reports 95% confidence sets obtained by inversion of the same null-imposed bootstrap-t tests.

Table 3. Core fixed-effects estimates and primary wild-cluster inference

Model	Regressor	β	Cluster SE	Wild p	Wild-bootstrap-t 95% CI	Holm p	LOO β range
Domestic	Capital intensity	0.2249	0.0837	0.0016	[0.027, 0.423]	0.0064	0.180–0.274
Domestic	Overdue-payables pressure	−0.0675	0.0277	0.0376	[−0.123, −0.012]	0.0492	−0.080 to −0.053
Domestic	Net entry rate	−0.00664	0.00196	0.0026	[−0.0112, −0.0021]	—	−0.0083 to −0.0059
Export	Graduate-flow intensity	0.9704	0.2637	0.0108	[0.407, 1.534]	0.0324	0.829–1.081
Export	SME employment scale	2.6171	0.9051	0.0246	[0.408, 4.826]	0.0492	2.221–3.494

Note: Primary p-values are 9,999-repetition null-imposed Stata boottest results clustered by region. Rademacher weights, the default symmetric two-sided p-value convention [ptype(symmetric)], and level(95) are used. The reported 95% confidence sets are obtained by inversion of the same restricted bootstrap-t tests. Seeds are 6101, 6102 and 6103 for the domestic coefficients and 6201 and 6202 for the export coefficients. LOO = leave one region out. Net entry is a control and is not included in the Holm family.

The additional cross-sectional-dependence check uses two-way clustering by region and year. Capital intensity remains below 5% (p=0.010), as do graduate-flow intensity (p=0.002) and SME employment scale (p=0.024). Overdue-payables pressure weakens to p=0.071; its two-way 95% interval is [−0.142, 0.007]. Applying Holm adjustment to the four substantive two-way p-values gives 0.031 for capital, 0.009 for graduate flow, 0.049 for employment and 0.071 for overdue payables. The dependence-robust check therefore leaves three screening conclusions unchanged but confirms that the overdue-payables criterion is the least secure. It is retained only as a provisional signal and is explicitly removed in the criterion-set sensitivity analysis.

The secondary checks do not support treating the four signals as equally strong. Capital is the most stable domestic result: it remains positive in denominator-safe and alternative-scale specifications, remains below 5% under two-way region–year clustering (p=0.010), but does not survive first differencing under few-cluster inference (wild p=0.420). Overdue-payables pressure weakens when the common denominator is removed (wild p=0.1689), is marginal under two-way clustering (p=0.071), and is uninformative in first differences (wild p=0.684). Graduate-flow intensity remains below 5% under two-way clustering (p=0.002) and is strong under alternative export outcomes, but loses precision in the 2013–2022 restriction and in first differences (wild p=0.441). SME employment is the most persistent dynamic signal: it remains below 5% under two-way clustering (p=0.024) and remains strongly significant in first differences (wild p=0.0009). This asymmetry motivates criterion-set sensitivity and the separation of employment from the need score.

4.2 Baseline need priorities and separate implementation scale

For the baseline decision-state window (underlying lagged criterion years 2019–2021), entropy assigns 0.504 to capital-intensity shortfall, 0.322 to overdue-payables burden and 0.174 to graduate-flow shortfall. CRITIC is flatter at 0.355, 0.355 and 0.290. These are information weights only. The higher entropy weight on capital means that the capital-shortfall column is more discriminatory across regions in this window; it does not imply that capital support has the largest social return.

Table 4. Evidence-strength qualifications used in the decision design

Variable/block	Dependence / dynamic robustness	Result	Decision-design implication
Capital intensity	Two-way region×year clustering; first differences; denominator-safe / alternative scale	Two-way p=0.010; FD wild p=0.420; denominator-safe wild p=0.0136 / 0.0335	Strongest domestic screening signal; level association, not a short-run treatment effect
Overdue-payables pressure	Two-way region×year clustering; first differences; denominator-safe models	Two-way p=0.071; FD wild p=0.684; denominator-safe wild p=0.1689 / 0.2232	Provisional need signal; strict criterion-set sensitivity excluding it is essential
Graduate-flow intensity	Two-way region×year clustering; 2013–2022 restriction; alternative export outcomes; first differences	Two-way p=0.002; full-sample alternatives strong; FD wild p=0.441	Need signal with temporal and short-run caveat
SME employment scale	Two-way region×year clustering; 2013–2022 restriction; first differences	Two-way p=0.024; FD wild p=0.0009	Separate implementation-scale descriptor; most persistent dynamic export-side signal
Institutional exposure	Placebo lead and trend-adjusted specifications	Identification checks fail	Excluded from decision matrix

Note: FD = first differences.

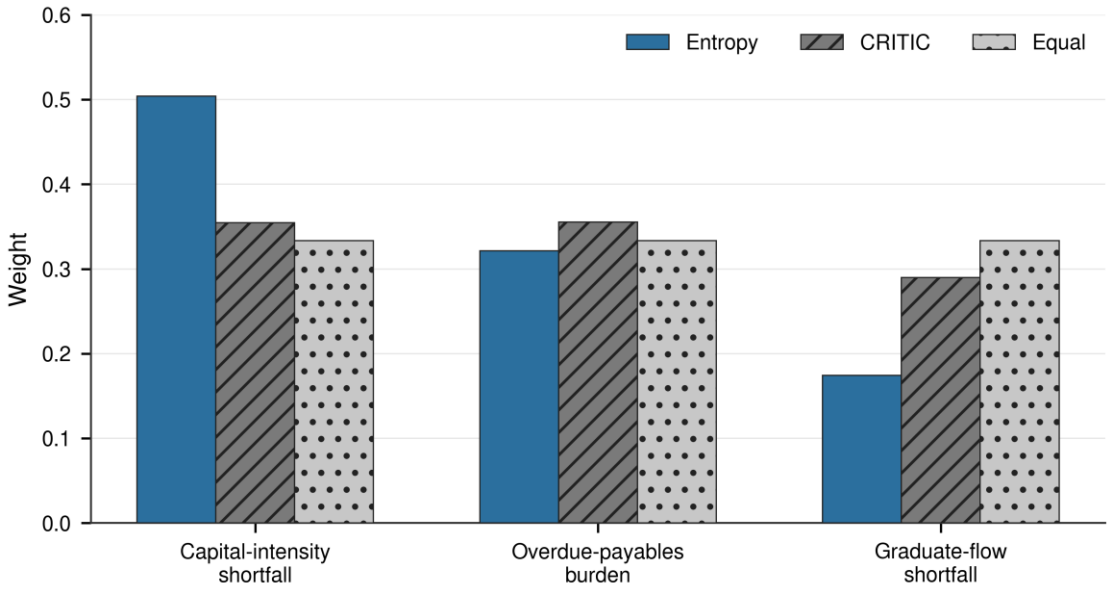


Figure 2. Information weights for the three need criteria.

Table 5. Need-criterion weights

Need criterion	Entropy	CRITIC	Equal
Capital-intensity shortfall	0.504	0.355	0.333
Overdue-payables burden	0.322	0.355	0.333
Graduate-flow shortfall	0.174	0.290	0.333

The baseline need ranking places Andijan first under WSM, WPM and TOPSIS. Kashkadarya and Fergana occupy the next two positions, with their order changing across operators. Keeping SME employment outside the score changes

the interpretation of several regions. Samarkand, for example, has the largest normalized employment scale but ranks ninth on entropy-weighted WSM need. Navoi ranks fifth on need but last on implementation scale. These cases demonstrate why a large beneficiary base should not compensate for weak evidence of regional need.

Table 6. Baseline need ranking and separate SME implementation scale

Region	WSM rank	WPM rank	TOPSIS rank	WSM need score	Employment-scale rank	Employment scale (0–1)
Andijan	1	1	1	0.913	3	0.915
Kashkadarya	2	2	3	0.767	4	0.865
Fergana	3	3	2	0.705	2	0.991
Namangan	4	5	5	0.586	5	0.843
Navoi	5	4	4	0.579	14	0.000
Surkhandarya	6	10	8	0.541	7	0.764
Khorezm	7	6	7	0.537	10	0.580
Karakalpakstan	8	7	6	0.536	11	0.525
Samarkand	9	8	9	0.504	1	1.000
Bukhara	10	9	10	0.440	9	0.593
Tashkent region	11	12	11	0.396	6	0.815
Syrdarya	12	11	13	0.375	13	0.096
Jizzakh	13	13	14	0.272	12	0.401
Tashkent city	14	14	12	0.205	8	0.638

Note: Need score uses only capital shortfall, overdue burden and graduate-flow shortfall. SME employment is displayed separately and does not enter any need rank.

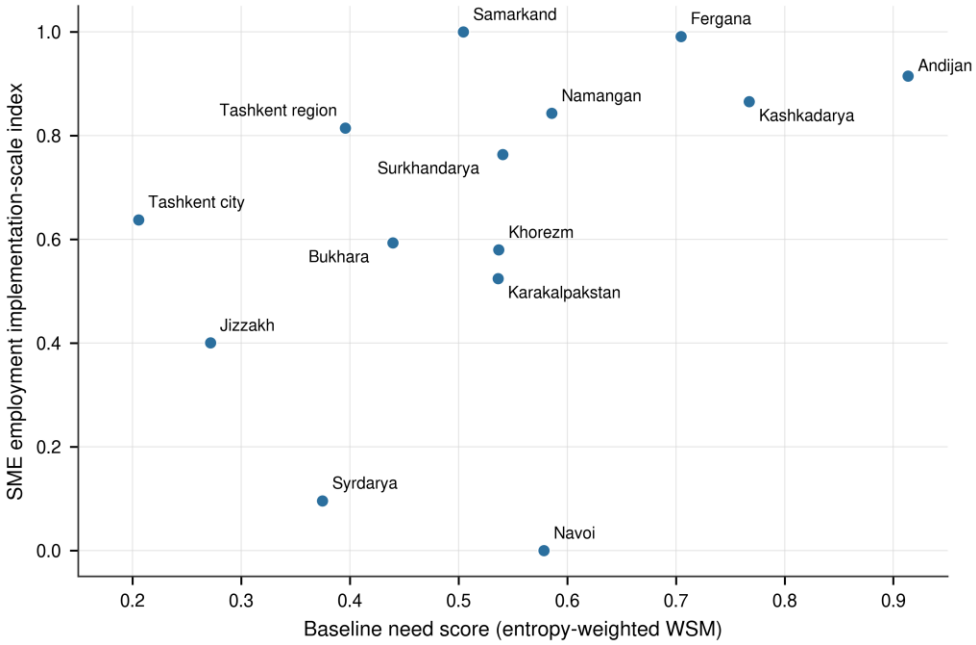


Figure 3. Need priority and SME implementation scale are distinct dimensions.

4.3 Structural robustness: normalization, weighting, aggregation and WPM floor

The expanded structural analysis contains 54 variants: three normalization rules, three weighting schemes, WSM and TOPSIS, plus WPM evaluated at four positive floors. The baseline top-three set—Andijan, Fergana and Kashkadarya—is preserved in 53 of 54 variants. The single exception is rank-percentile normalization with CRITIC weights and TOPSIS, where Tashkent region ranks third and Kashkadarya fourth. Andijan remains first in every variant, Fergana ranges only from second to third, and Kashkadarya from second to fourth. The result therefore supports a highly stable first position and a strong leading group, but not an invariant top-three set under every structural assumption.

Table 7. Rank robustness across 54 structural variants

Region	Best	Worst	Mean rank	P(top 3)	P(top 5)
Andijan	1	1	1.00	1.000	1.000
Fergana	2	3	2.22	1.000	1.000
Kashkadarya	2	4	2.80	0.981	1.000
Namangan	4	8	5.24	0.000	0.630
Khorezm	4	8	5.63	0.000	0.500
Samarkand	4	9	6.57	0.000	0.204
Navoi	4	10	6.78	0.000	0.259
Tashkent region	3	12	8.41	0.019	0.333
Karakalpakstan	6	13	9.13	0.000	0.000
Surkhandarya	5	13	10.09	0.000	0.074
Syrdarya	8	13	10.46	0.000	0.000
Bukhara	9	14	10.80	0.000	0.000
Jizzakh	10	14	12.52	0.000	0.000
Tashkent city	9	14	13.35	0.000	0.000

Note: Variants combine min–max, vector-distance and rank-percentile normalization; entropy, CRITIC and equal weights; WSM, WPM and TOPSIS; WPM floors 0.01, 0.05, 0.10 and 0.20. Pairwise Spearman correlations across the 54 rankings range from 0.451 to 1.000 (mean 0.839).

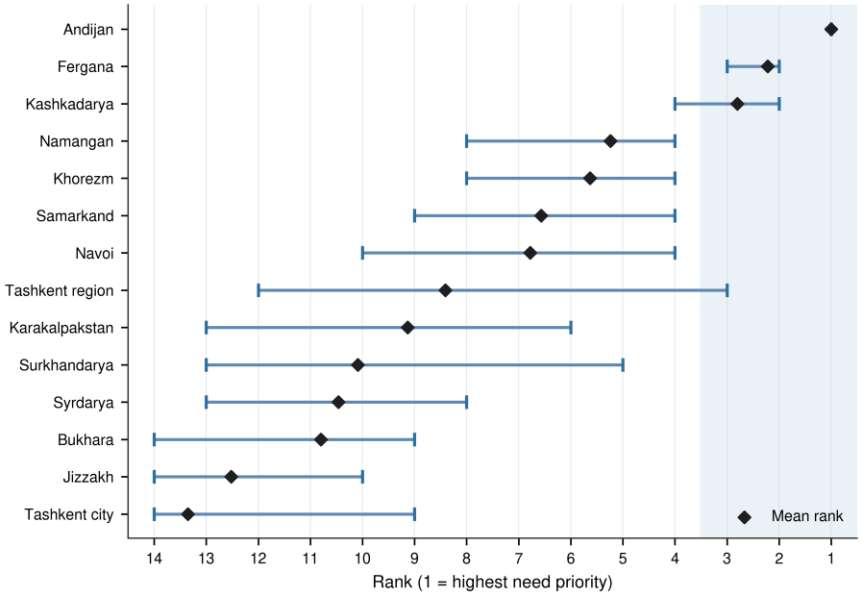


Figure 4. Rank ranges across 54 structural MCDM variants.

4.4 Criterion-set uncertainty and the exclusion of net entry

Criterion-set sensitivity is more informative than a single fixed-set ranking because the econometric evidence is uneven. All seven non-empty subsets of the three need criteria are evaluated. With all three need criteria, Andijan, Fergana and Kashkadarya form the top-three set in all nine weight–aggregation combinations under min–max normalization. The same set survives when graduate-flow shortfall is removed and also appears under capital alone. When overdue-payables burden is removed, however, Surkhandarya enters the top three in five of nine variants and Fergana in four. The overdue + graduate-flow subset produces a very different pattern: Andijan and Tashkent region are top-three in all nine variants, Fergana in six, Samarkand in two and Tashkent city in one. The ranking therefore depends materially on whether the strongest capital signal is present, and the weaker overdue criterion affects third-place membership when capital is combined with graduate flow.

Table 8. Criterion-set sensitivity

Criterion set	Leading pattern	Observed stability	Interpretation
All three need criteria	Andijan; Fergana; Kashkadarya	A/F/K top three in 9/9 variants	Baseline
Capital + overdue	Andijan; Fergana; Kashkadarya	A/F/K top three in 9/9	Graduate-flow inclusion does not drive leading set
Capital + graduate-flow	Kashkadarya; Andijan; Surkhandarya/Fergana	Surkhandarya top-three in 5/9; Fergana in 4/9	Third-place membership depends partly on overdue burden
Overdue + graduate-flow	Andijan; Tashkent region; Fergana/Samarkand/Tashkent city	Andijan and Tashkent region top-three in 9/9; Fergana 6/9; Samarkand 2/9; Tashkent city 1/9	Without capital, the leading set changes substantially
Capital only	Kashkadarya; Andijan; Fergana	Same three regions	Capital provides a strong core signal
Single overdue / single graduate-flow	Very different regional orders	Large changes	Single weaker/partial criteria are insufficient for a robust priority claim

Net entry provides a complementary falsification-style decision test. If high entry is treated as a churn or fragmentation burden, Navoi becomes the leading region (mean rank 1.22) while Andijan falls to mean rank 5.11. If low entry is treated as a deficit in entrepreneurial dynamism, Andijan and Fergana rank first and second and Namangan/Kashkadarya compete for third. The same econometric coefficient therefore supports sharply different priorities depending on the policy orientation imposed. This result is the empirical reason for keeping net entry outside the core decision matrix.

4.5 Weight uncertainty beyond the entropy neighbourhood

Entropy-centred Dirichlet simulations reproduce the familiar Andijan–Kashkadarya–Fergana group because the draws are concentrated around the final three-criterion entropy vector. Under $\kappa=20$, the top-three probabilities are 1.0000 for Andijan, 0.9997 for Fergana and 0.9993 (99.93%) for Kashkadarya; they approach one under $\kappa=50$ and 100. The 99.93% value is the result from the final three-criterion need specification and is used consistently in the manuscript, response letter and supplementary workbook. These simulations demonstrate local stability around entropy, not robustness across all plausible policy weights.

The uniform-simplex experiment is deliberately more demanding. With weights drawn from Dirichlet(1,1,1), Andijan remains in the top three in 99.31% of 10,000 draws and has a 5th–95th rank interval of 1–2. Fergana's top-three probability is 79.46% (rank interval 2–5) and Kashkadarya's is 73.42% (1–6). Tashkent region and Surkhandarya enter the top three in 27.16% and 16.99% of draws, respectively. Thus the first-ranked region is preference-robust, while the composition of the wider high-priority band is partly preference-dependent once the full weight simplex is admitted.

Table 9. Rank acceptability under uniform sampling over the weight simplex

Region	P(top 3)	P(top 5)	Mean rank	5–95% rank
Andijan	0.993	1.000	1.27	1–2
Fergana	0.795	0.955	3.13	2–5
Kashkadarya	0.734	0.926	2.82	1–6
Tashkent region	0.272	0.403	7.16	2–12
Surkhandarya	0.170	0.448	7.35	2–14
Tashkent city	0.018	0.057	12.82	5–14

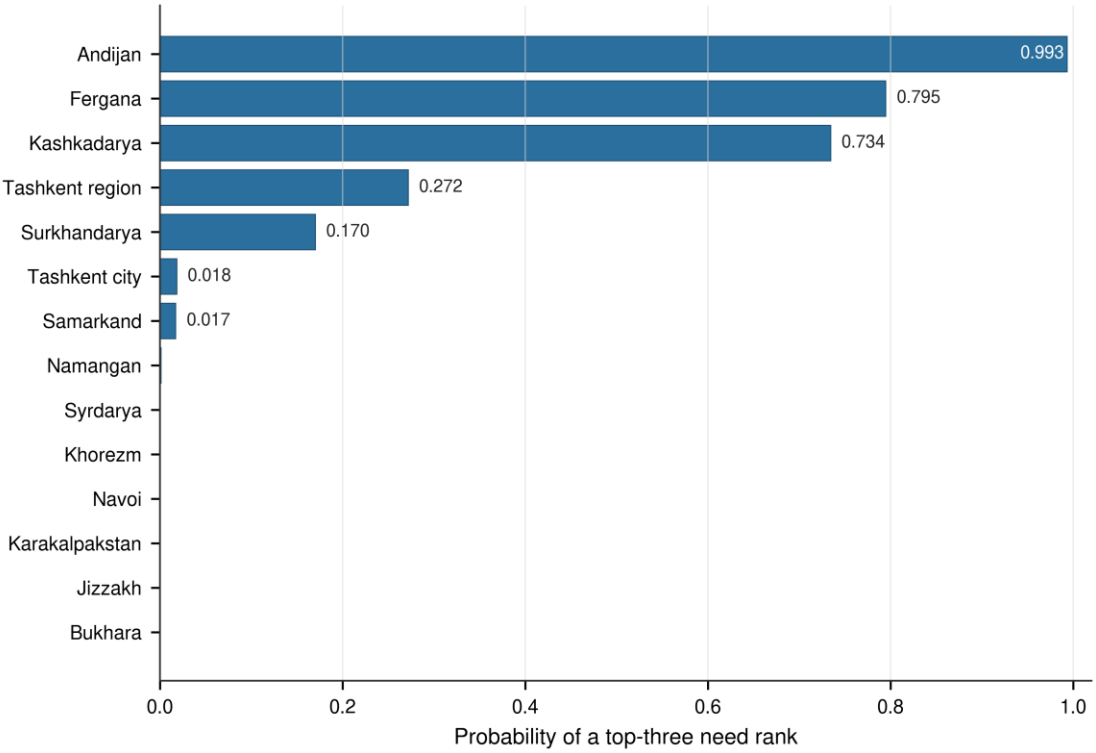


Figure 5. Top-three probabilities under unrestricted Dirichlet(1,1,1) weight uncertainty.

4.6 Decision-window sensitivity

Temporal sensitivity changes the policy interpretation most sharply. The baseline ranking is not a time-invariant regional taxonomy. Earlier three-year windows place substantial weight on overdue-payables dispersion and often elevate Syrdarya or Namangan. Rank correlation with the 2020–2022 model-row baseline rises from 0.130 for 2013–2015 to 0.640 for 2019–2021. In the latest baseline, the top group becomes Andijan, Kashkadarya and Fergana. Because the regressors are lagged, the 2020–2022 model rows correspond to underlying criterion states from 2019–2021.

Table 10. Recent rolling-window need rankings

Model-row window	Underlying lagged criterion years	Spearman vs latest	Top-three need set
2017–2019	2016–2018	0.200	Andijan; Namangan; Syrdarya
2018–2020	2017–2019	0.490	Andijan; Syrdarya; Namangan
2019–2021	2018–2020	0.640	Andijan; Syrdarya; Fergana
2020–2022	2019–2021	1.000	Andijan; Kashkadarya; Fergana

Note: Earlier windows 2013–2015 through 2016–2018 are reported in the supplementary workbook. The temporal variation means that the historical baseline is not a current funding recommendation; a live application requires rolling re-estimation with harmonized current data.

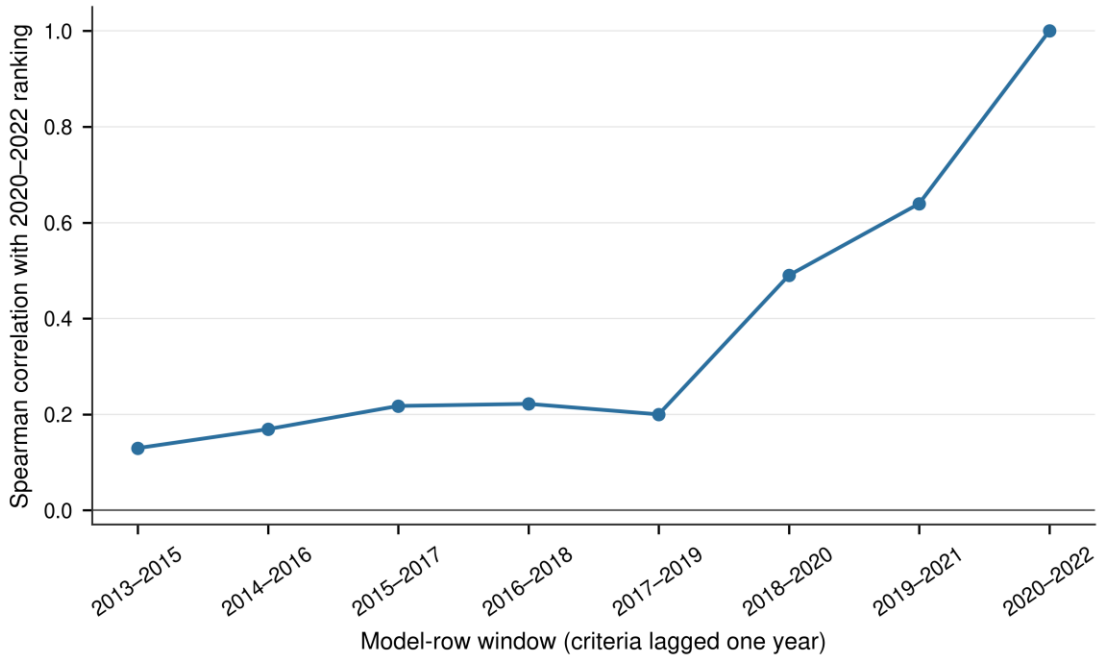


Figure 6. Temporal stability of regional need ranks across rolling three-year windows.

5. Discussion

The empirical results support a layered rather than a single-score decision structure. The econometric stage identifies capital intensity, overdue-payables pressure, graduate-flow intensity and SME employment as stable full-sample correlates under the primary few-cluster inference. The decision stage does not treat those four variables as equivalent allocation criteria. Three are mapped into need only after explicit policy-orientation assumptions, while employment remains a separate implementation-scale descriptor. Capacity therefore cannot compensate mechanically for low need.

Recent work has already combined panel regression with MCDM in regional analysis (Profiroiu et al., 2025), and robust MCDM under uncertainty is well established (Lotfi et al., 2023; Więckowski & Sałabun, 2023, 2024). The contribution here is therefore deliberately narrower: the sequencing and auditability of the hybrid design. An econometric coefficient admits or excludes a candidate from further consideration; it does not set the sign of priority or the criterion weight. Policy orientation is stated separately. Entropy and CRITIC then describe the information structure of the decision matrix. Finally, sensitivity analysis asks how much the resulting priority judgement depends on those choices. This separation reduces the risk of circular reasoning in which regional dispersion appears first as statistical evidence, again as a large information weight, and is then mistakenly labelled policy importance.

The empirical pattern is strongest for Andijan. It ranks first under all 54 structural variants and is top-three in 99.31% of unrestricted weight draws. Fergana and Kashkadarya also form a strong baseline leading group, but their wider stability is less absolute: Kashkadarya drops to fourth in one structural variant, and unrestricted weight sampling gives top-three probabilities below 0.80 for both. This distinction is operationally useful. A decision maker can treat Andijan as a highly stable need signal under the model, while viewing membership of the remainder of the leading tier as conditional on policy preferences and the selected criteria.

Criterion-set analysis provides an additional layer of caution. The capital result is the most econometrically stable and, by itself, still identifies Kashkadarya, Andijan and Fergana as the leading shortfall regions. Overdue-payables pressure is the only substantive coefficient that no longer clears 5% under two-way region–year clustering ($p=0.071$), and it is also weaker in denominator-safe regressions. Removing it changes the third-place pattern, allowing Surkhandarya to displace Fergana in several variants. Graduate-flow intensity is period-sensitive and does not survive first differencing, but removing it leaves the baseline leading set intact. The appropriate conclusion is therefore not that every retained criterion is equally validated; rather, the ranking can be decomposed into a robust capital-driven core and additional financial-stress and skills-supply information whose influence is explicitly visible.

The net-entry experiment reinforces the same principle. The regression supplies a stable negative coefficient, but the decision meaning of high entry is ambiguous. Treating high entry as harmful churn makes Navoi the leading priority, while treating low entry as a deficit yields a very different ordering. Because the empirical model cannot identify which policy interpretation is appropriate, exclusion is more defensible than pretending that statistical significance resolves the normative choice. This is precisely the type of ambiguity an admission-orientation architecture is designed to expose.

Temporal sensitivity has the clearest implication for managerial use. The baseline decision state is derived from 2019–2021 criterion values, not from contemporaneous 2026 data. Earlier windows produce materially different rankings, indicating that regional priorities evolve with the distribution of constraints. The framework should therefore be implemented as a rolling monitoring process rather than as a permanent allocation map. A ministry using it operationally would update the source data, re-run the econometric screen when enough new years accrue, recalculate the decision matrix, and compare the new priority band with the previous one. Changes in rank would then be treated as information about changing regional conditions rather than as model failure.

The analysis does not recommend instrument-specific spending. A capital shortfall can motivate closer investigation of equipment finance, guarantees or credit conditions, but the present regressions do not estimate the treatment effect of those programmes. Overdue-payables pressure may point to liquidity or payment-discipline problems, and graduate-flow shortfall to skills-supply constraints, yet programme design requires additional evidence on costs, take-up, implementation capability and heterogeneous firm responses. Proportional budget shares and instrument prescriptions are therefore not reported as empirical findings. MCDM outputs are used to organize managerial attention, not to substitute for programme evaluation.

Several limitations remain. First, the cross-section contains only 14 regions. Wild-cluster procedures improve inference but do not create the information available in a large-cluster panel. Second, regional averages conceal firm-level heterogeneity in sector, age, size, ownership and managerial capability. Third, the domestic sales-intensity numerator and active-entity scale come from related official series whose statistical scopes are not perfectly identical; denominator-safe robustness reduces but does not eliminate this measurement limitation. Fourth, the regressions are associational. Fixed effects control time-invariant regional heterogeneity and common shocks, but time-varying confounding and reverse causality cannot be ruled out. Fifth, the need orientations are normative assumptions tied to a constraint-relief objective, not revealed preferences or welfare weights. Finally, the Uzbekistan application is institutionally specific. The architecture is portable, but the admissible variables, orientations and policy thresholds must be re-established in each setting.

6. Conclusion

This study develops an econometric-screening and robust-MCDM framework for regional small-business support decisions. The architecture treats empirical admissibility, policy orientation, information weighting and implementation scale as four different analytical tasks. That separation is decisive. Fixed-effects coefficients are used to screen candidate regional signals; they are not converted mechanically into need or funding weights. Three screened variables—capital-intensity shortfall, overdue-payables burden and graduate-flow shortfall—form the need matrix, while SME employment is reported separately as implementation scale.

The baseline application identifies Andijan, Kashkadarya and Fergana as the leading need group. Robustness is strongest for Andijan: it ranks first in all 54 structural variants and remains top-three in 99.31% of unrestricted weight draws. Fergana and Kashkadarya remain strong candidates but are more preference-sensitive. Criterion-set tests show that capital provides the most stable core signal, while the influence of overdue-payables pressure should be interpreted more cautiously. Rolling-window results show that the ranking changes materially over time, which rules out treating the 2019–2021 decision state as a current or permanent budget map.

The framework therefore produces decision-support priorities, not optimal allocation shares. Its practical value lies in making the chain of judgement auditable: which variables enter, why their direction is defined as need, how information weights are formed, how rankings react to modelling choices, and whether implementation scale supports or constrains programme delivery. A live system should update that chain with current harmonized data and connect regional prioritization to programme-level causal evaluation before specific funding amounts are assigned.

7. Future Research

The next step is to combine the regional need screen with explicit operational constraints. A constrained optimization model could incorporate programme costs, minimum regional coverage, equity objectives, diminishing returns and administrative capacity after those parameters are elicited from the decision authority. Firm-level data would allow regional need to be linked to beneficiary selection and heterogeneity within regions. Most importantly, future programme assignments and post-support outcomes would permit causal evaluation of specific instruments, creating a feedback loop in which the screening layer is informed by realized treatment effects rather than by regional performance associations alone.

Author Contributions

Conceptualization, A.S. and I.A.; methodology, A.S. and I.A.; software, A.S.; formal analysis, A.S.; data curation, A.S.; writing—original draft preparation, A.S.; writing—review and editing, I.A.; supervision, I.A. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The supplementary replication package contains the frozen regional panel, source documentation identifying the underlying National Statistics Committee/SIAT series, variable-construction notes, the need matrix, primary bootstrap confidence sets and seeds, two-way region–year dependence-robust results, first-difference wild-cluster inference, all seven criterion-subset results, structural and rolling-window sensitivity results, weight-uncertainty simulations, and reproducibility code. The underlying source series are official aggregate statistics and contain no individual-level confidential data.

Ethical considerations

The study uses aggregated regional secondary statistics and does not involve human participants, individual-level personal data or animal subjects. No separate human-subject ethics approval was required for the reported analysis.

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Conflict of interest

The authors declare no conflict of interest.

Declaration of Generative AI and AI-assisted technologies in the writing process

OpenAI ChatGPT was used for language editing and coding assistance during manuscript preparation. The authors subsequently reviewed and verified the text, data, econometric outputs, code, figures and references and take full responsibility for the content.

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