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## **DECOMPOSING PRODUCTIVITY GROWTH IN KAZAKHSTAN'S REGIONS: TECHNOLOGICAL PROGRESS AND RESOURCE-USE EFFICIENCY**

### **Abstract**

Kazakhstan's regional innovation policy, including its Smart Specialisation and Quadruple Helix approaches, relies predominantly on static indicators, leaving the separate contributions of technological change and efficiency catch-up to productivity dynamics unexamined. This study decomposes total factor productivity (TFP) change in the innovation systems of Kazakhstan's regions into efficiency-catch-up and technological-change components using a Malmquist-DEA framework, and identifies the spatial and structural determinants of this change. The research hypothesis is that the average decline in regional innovation productivity over 2014–2024 is driven predominantly by technological regress (a contracting production frontier) rather than efficiency catch-up, and that this process is institutional rather than geographic in nature. The study draws on an official panel from the Bureau of National Statistics of the Republic of Kazakhstan for 2014–2024 across 17 regions (187 observations), combining panel regression, Malmquist-DEA decomposition, spatial autocorrelation analysis, principal component and cluster analysis, and explainable machine learning (Random Forest, gradient boosting, CatBoost with SHAP). Results show that the geometric-mean TFP change between 2014–2016 and 2022–2024 was 0.662, driven predominantly by technological regress (0.543) and partly offset by positive efficiency catch-up (1.219). No significant global spatial autocorrelation of productivity change was detected (Moran's  $I = 0.148$ ;  $p = 0.436$ ), confirming an institutional rather than geographic diffusion mechanism. The findings indicate that Kazakhstan's Smart Specialisation and GovTech/AI Governance policies should be reoriented toward technological renewal rather than efficiency improvement alone.

**Keywords:** regional innovation system, Malmquist index, DEA, Smart Specialisation, Quadruple Helix, AI Governance, machine learning.

## Introduction

Regional innovation policy across the OECD and emerging economies has converged on a shared institutional vocabulary: Smart Specialisation (S3) as the mechanism for prioritising regional research and innovation domains through an entrepreneurial discovery process [1, 2]; the Quadruple Helix as the coordination model linking government, industry, academia and civil society [3]; and, increasingly, GovTech and AI Governance as the digital-institutional infrastructure through which these priorities are monitored and adjusted [4, 5]. Kazakhstan has formally adopted elements of this vocabulary in its national science and innovation strategy, and the author's own prior work has proposed an intelligent, AI-supported architecture for regional innovation monitoring consistent with this agenda. Yet the empirical evidence base underpinning these policy instruments in Kazakhstan remains predominantly static: regional innovation performance is assessed through cross-sectional indicators: R&D spending, the number of innovating enterprises, innovation-activity rates, measured at a point in time, without decomposing how much of any observed change reflects genuine technological renewal as opposed to regions simply moving closer to (or further from) an already-existing production frontier.

This distinction is not a technical nicety. Smart Specialisation presumes that regions can be steered toward domains of comparative technological advantage through policy coordination [1]; Quadruple Helix and GovTech instruments presume that better orchestration of actors and data can lift regions toward an existing best-practice frontier [3, 4]. Neither presumption is informative if the frontier itself is stagnant or contracting: in that case, no amount of governance or coordination improvement (efficiency catch-up) can substitute for renewed investment in the technological base itself. Malmquist-DEA productivity analysis, widely used in innovation-system and regional-competitiveness research internationally to separate these two channels [6], has not, to the author's knowledge, been applied to Kazakhstan's regional innovation systems – a gap this study addresses.

The aim of this study is to decompose total factor productivity (TFP) change in the innovation systems of Kazakhstan's regions into efficiency-catch-up and technological-change components, and to identify the spatial and structural determinants of this change, situating the results within the Smart Specialisation, Quadruple Helix and GovTech/AI Governance policy discourse. The research hypothesis (H1) is that the average decline (if any) in regional innovation productivity over 2014–2024 is driven predominantly by technological regress rather than by efficiency catch-up – an 'investment-output decoupling' pattern consistent with, but distinct from, the level-based resource-scale findings of prior cross-sectional work. Two supporting hypotheses are tested: (H2) productivity change shows no significant spatial autocorrelation, reinforcing an institutional rather than geographic-spillover account of regional divergence, with direct implications for whether Smart Specialisation and GovTech instruments should be designed around neighbourhood effects or targeted region-by-region; (H3) machine-learning models can reliably and interpretably attribute cross-sectional efficiency variation to structural features, providing an evidence base for the kind of explainable, audit-ready decision-support layer that AI Governance frameworks require of algorithmic inputs to public policy [5, 7].

The corresponding research questions are: (RQ1) how much of the change in regional innovation productivity over the past decade reflects technological change as opposed to efficiency catch-up, and is there evidence of diminishing returns to R&D scale; (RQ2) does productivity change cluster spatially among neighbouring regions; (RQ3) which structural features explain cross-sectional efficiency differences, and with what degree of statistical confidence given the small number of regional units; (RQ4) what do these results imply for the sequencing and targeting of Smart Specialisation, Quadruple Helix and GovTech/AI Governance instruments in Kazakhstan. The scientific novelty of the study lies in (i) the first application of Malmquist-DEA productivity decomposition to Kazakhstan's regional innovation systems; (ii) an explicit, pre-registered-style test of factor-analytic adequacy (KMO, Bartlett) before applying dimension-reduction methods, avoiding the common practice of running factor analysis regardless of sample adequacy; (iii) a comparative machine-learning exercise, using Random Forest, gradient boosting and CatBoost, explaining cross-sectional DEA efficiency scores, interpreted via SHAP; and (iv) an explicit reframing of these results within the Smart Specialisation/Quadruple Helix/GovTech/AI Governance policy vocabulary, an integration largely absent from the existing Kazakhstani literature. The practical significance lies in clarifying whether regional innovation policy instruments in Kazakhstan should prioritise technological-renewal investment (infrastructure,

international technology transfer, R&D-intensive Smart Specialisation domains) or governance/coordination reform (Quadruple Helix orchestration, GovTech monitoring) – a distinction current policy discourse does not make explicit.

## Materials and methods

Smart Specialisation, formalised in EU cohesion policy after Foray et al. [1] and McCann and Ortega-Argiles [2], directs regions to identify a small number of domains where an entrepreneurial discovery process reveals genuine comparative advantage, rather than replicating generic innovation-policy menus across regions. Balland et al. [8] show, using European regional patent data, that specialisation choices consistent with a region's existing technological relatedness outperform those that are not – a finding with direct implications for interpreting Kazakhstan's regional innovation-output composition (Section on results). The Quadruple Helix model extends the earlier Triple Helix university-industry-government framework by adding civil society as a co-producer of innovation [3]. Applied to post-Soviet and Central Asian innovation systems, this lens typically reveals a strong-government, weak-civil-society/industry linkage profile, a pattern this study returns to in the Discussion.

GovTech – the use of digital government platforms to deliver and monitor public services and policy instruments - has been positioned by the World Bank and OECD as the operational infrastructure through which data-driven regional policy, including Smart Specialisation monitoring, becomes feasible at scale [4, 9]. AI Governance frameworks (OECD AI Principles; the EU AI Act's risk-tiered approach; UNESCO's Recommendation on the Ethics of Artificial Intelligence) increasingly require that algorithmic inputs to public-sector decisions, including regional-policy scoring and ranking tools, be explainable and auditable [5, 10, 11]. Kazakhstan's own digital-government and AI-strategy documents reference these frameworks, but the empirical, quantitative layer that would let a GovTech platform actually monitor regional innovation productivity, as opposed to activity levels, has not been built. Recent Scopus/Web of Science literature (2020–2026) on digital transformation and regional innovation systems emphasises that digital infrastructure is a necessary but not sufficient condition for innovation-productivity growth [12], and that resource-dependent regions in particular exhibit an 'innovation paradox' in which substantial R&D spending fails to translate into broad-based productivity gains [13, 14, 15] – a pattern this study tests directly at the productivity-decomposition level for Kazakhstan.

Methodologically, Malmquist-DEA productivity decomposition, introduced by Fare et al. [6] building on Charnes, Cooper and Rhodes' original DEA formulation [16], remains the standard tool for separating efficiency catch-up from technological change in cross-country and cross-region innovation-system studies [6]; recent applications extend it to national innovation systems under digital transformation [12]. Explainable machine learning (SHAP [17]) has become the standard companion to tree-ensemble models (Random Forest [19], XGBoost [20], CatBoost [21]) in policy-relevant applications precisely because AI Governance frameworks require interpretability [5, 7]. This study combines these two literatures, dynamic efficiency decomposition and explainable machine learning, within Kazakhstan's Smart Specialisation/Quadruple Helix/GovTech policy context for the first time.

The data source is official statistics from the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan [18] for 2014–2024 across 17 territorial units (14 regions and 3 cities of republican significance). A balanced panel of 187 observations (17 x 11 years) was built for gross domestic R&D expenditure (GERD, mln KZT), the number of innovating enterprises (NOEI, units), the volume of innovative products (VOIP, mln KZT), and the enterprise innovation-activity rate (IAR, %). Patent counts for 2024 were obtained from the National Institute of Intellectual Property of Kazakhstan for the cross-sectional composite-index analysis. GERD, NOEI and VOIP were log-transformed given pronounced right skew (2.9–4.3).

Method selection followed the nature of the data and the research questions, with explicit justification and, where a method proved inapplicable, an explicit alternative. Pearson and Spearman correlations were computed given partial departure from normality. Fixed-effects (FE) and random-

effects (RE) panel models were estimated for IAR on  $\log(\text{GERD})$ ,  $\log(\text{NOEI})$ ,  $\log(\text{VOIP})$  and a year trend, with the Hausman test used to select the consistent specification [22] and an F-test for poolability. A quadratic specification (centred  $\log(\text{GERD})$  and its square) was added to test for diminishing returns to R&D scale, following the logic of Nickell's [23] critique of naive dynamic panel estimation. The quadratic terms were mean-centred to avoid mechanical collinearity with their square, and joint significance was assessed via a Wald test.

Dynamic productivity change was assessed via a Malmquist-DEA decomposition [6, 17], computed between the 2014–2016 and 2022–2024 three-year averages (rather than single years) to reduce the influence of the well-documented single-year volatility of regional innovation-output statistics, particularly for resource regions subject to large one-off contracts. Given data availability, the DEA specification uses GERD as the sole input and NOEI and VOIP as outputs (patents, available only for 2024, could not be included in a two-period design without fabricating a 2014 value, and were therefore excluded from this component). Input-oriented CCR distance functions were computed for each region in each period against both the same-period and cross-period frontiers, yielding the standard geometric-mean decomposition of the Malmquist index into efficiency change (catch-up) and technological change (frontier shift) [6]. As a robustness check, the decomposition was also computed on single-year (2014 vs 2024) data. The direction of both components was consistent with the smoothed specification.

For the 2024 cross-section, prior to applying any dimension-reduction technique, sampling adequacy was tested explicitly: Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy [24] were computed for the five-indicator set (GERD, NOEI, patents, IAR, VOIP). Because KMO fell below the conventional 0.6 adequacy threshold (Results), exploratory factor analysis was not pursued as a substantive method. Principal component analysis (PCA), which does not require the same common-factor-model assumptions and is more robust in small samples, was retained instead. Structural equation modelling (SEM/PLS-SEM) was ruled out on the same small-sample grounds ( $n = 17$  with a single indicator set), consistent with the general guidance that PLS-SEM requires substantially larger samples and multiple reflective indicators per construct [25].

Hierarchical clustering (Ward's method) was cross-validated against independent K-means clustering ( $k = 4$ , selected by silhouette score) via the Adjusted Rand Index. A composite regional innovation-development index was constructed and compared under two independent objective weighting schemes: PCA-based weights (proportional to squared PC1 loadings) and entropy weights (objective, information-theoretic weighting [26]). The Analytic Hierarchy Process [27] was not applied independently, to avoid reconstructing expert pairwise judgements that were never elicited. Regional ranking used TOPSIS [28] under both weighting schemes, compared via Spearman rank correlation. Static (2024) resource-conversion efficiency was assessed via DEA under both constant (CCR) and variable (BCC) returns to scale, with the CCR/BCC ratio giving scale efficiency.

Global spatial autocorrelation of both the 2024 IAR level and log Malmquist TFP change was tested via Moran's I [29] on a row-standardised, first-order (queen) contiguity matrix for the 17 units, with significance assessed by 999-permutation pseudo-p-values, following Anselin's local-indicator framework for interpretation [30].

Cross-sectional DEA efficiency (2022–2024 average) was modelled as a function of structural features ( $\log \text{GERD}$ ,  $\log \text{NOEI}$ ,  $\log \text{VOIP}$ , IAR, resource- and agglomeration-region dummies) using three tree-ensemble learners – Random Forest [19], gradient boosting implementing the XGBoost principle [20] (scikit-learn implementation), and CatBoost [21] – evaluated by leave-one-out cross-validation given the small sample ( $n = 17$ ). Feature attribution used SHAP [17]. The national IAR time series (11 annual observations) was tested for stationarity (augmented Dickey-Fuller) and modelled by ARIMA with order selected by AIC. Given the series length falls well short of the 40–50 observations usually recommended for reliable ARIMA identification, and Prophet requires longer, seasonally structured series, both models' outputs are treated as illustrative trend extrapolation. Difference-in-differences was judged inapplicable in the absence of an identifiable exogenous policy treatment and a corresponding regional control group. All computations used Python 3.9 (pandas, NumPy, SciPy, statsmodels, linearmodels, scikit-learn, factor\_analyzer, catboost, shap).

## Results and discussion

### Descriptive statistics, correlation and panel regression

Across the 2014-2024 panel ( $N = 187$ ), NOEI, VOIP and GERD show pronounced right skew (2.9–4.3), reflecting concentration of innovation activity in Almaty and Astana; IAR is close to symmetric. Pearson and Spearman correlations agree that IAR is not significantly related to  $\log(\text{GERD})$  ( $r = 0.140$ ,  $p = 0.056$ ;  $\rho = 0.105$ ,  $p = 0.151$ ) but is strongly related to  $\log(\text{NOEI})$  ( $r = 0.688$ ;  $\rho = 0.722$ ;  $p < 0.001$ ) - an early indication, consistent with the broader innovation-paradox literature on resource-dependent regions [13, 14, 15], that R&D scale alone is a weak lever for activity.

Table 1 – Fixed – and random-effects panel estimates (dependent variable: IAR, %)

| Regressor          | FE (within)      | RE               |
|--------------------|------------------|------------------|
| $\ln(\text{GERD})$ | 0.227 (0.146)    | -0.154 (0.216)   |
| $\ln(\text{NOEI})$ | 6.761*** (0.546) | 6.045*** (0.611) |
| $\ln(\text{VOIP})$ | 0.218** (0.106)  | 0.178* (0.100)   |
| Year (centred)     | 0.046 (0.042)    | 0.108** (0.051)  |
| R2 (within)        | 0.797            | 0.781            |
| N                  | 187              | 187              |

Note: Compiled by the authors.

Region-clustered robust SE in parentheses. \*\*\*  $p < 0.01$ ; \*\*  $p < 0.05$ ; \*  $p < 0.10$ . The Hausman test rejects RE consistency ( $\chi^2(4) = 17.99$ ;  $p = 0.0012$ ), so FE is the preferred specification; a poolability F-test ( $F(16,166) = 37.16$ ;  $p < 0.001$ ) confirms entity effects are required. As documented in prior cross-sectional work,  $\log(\text{NOEI})$  is the only consistently significant driver of IAR across specifications, while  $\log(\text{GERD})$  loses significance once time-invariant regional heterogeneity is controlled for.

Source: compiled by the authors based on data from the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan (<https://stat.gov.kz/ru/>) and the authors' own calculations

Table 2 reports the quadratic FE test for diminishing returns to R&D scale (centred  $\log(\text{GERD})$  and its square, controlling for  $\log(\text{NOEI})$  and year). The quadratic coefficient is negative, consistent with an eventually diminishing or negative marginal effect of R&D scale, but neither term is individually significant ( $p = 0.475$  and  $p = 0.173$ ) nor jointly significant (Wald  $\chi^2(2) = 3.57$ ;  $p = 0.168$ ). The implied turning point ( $\text{GERD}^*$  approx. 3,240 mln KZT, below which 65% of panel observations fall) is therefore suggestive rather than confirmed - an honest null result at the parametric, activity-level regression stage that motivates the nonparametric Malmquist decomposition below, which has greater power to detect frontier-level change.

Table 2 – Quadratic FE test of diminishing returns to R&D scale

| Regressor                      | Coef.    | SE    | p-value |
|--------------------------------|----------|-------|---------|
| $\ln(\text{GERD})$ , centred   | 0.102    | 0.142 | 0.475   |
| $\ln(\text{GERD})^2$ , centred | -0.102   | 0.074 | 0.173   |
| $\ln(\text{NOEI})$             | 6.925*** | 0.512 | < 0.001 |
| Year (centred)                 | 0.098**  | 0.039 | 0.012   |

Note: Compiled by the authors based on data from the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan and the authors' own calculations.

Region-clustered robust SE. Joint Wald test on the two GERD terms:  $\chi^2(2) = 3.57$ ,  $p = 0.168$  (not significant). VIF for the centred quadratic terms: 1.4–1.7 (no mechanical collinearity).

### Malmquist-DEA productivity decomposition, 2014–2016 to 2022–2024

Table 3 and Figure 1 report the Malmquist decomposition. The national geometric-mean TFP change is 0.662, a productivity decline of roughly a third over the decade, driven overwhelmingly by technological regress (geometric-mean technological change = 0.543, i.e. the estimated

production frontier itself contracted) and only partly offset by positive efficiency catch-up (geometric mean = 1.219). Only 5 of 17 regions show TFP improvement (Kostanay, Karaganda, West Kazakhstan, Almaty city, Atyrau), and technological change exceeds 1 (frontier expansion) in only 2 of 17 regions. This confirms H1: the productivity story of the past decade is one of frontier contraction, not efficiency failure. Efficiency catch-up was in fact widespread (9 of 17 regions improved), but could not compensate for a shrinking technological ceiling.

Table 3 – Malmquist-DEA decomposition, selected regions (input: GERD; outputs: NOEI, VOIP)

| Region                  | Eff. Change | Tech. change | Malmquist TFP |
|-------------------------|-------------|--------------|---------------|
| Atyrau                  | 9.293       | 0.658        | 6.114         |
| Karaganda               | 2.871       | 0.523        | 1.503         |
| Kostanay                | 1.000       | 1.360        | 1.360         |
| Almaty (city)           | 4.781       | 0.263        | 1.255         |
| Astana                  | 1.207       | 0.335        | 0.405         |
| North Kazakhstan        | 0.233       | 0.559        | 0.130         |
| National geometric mean | 1.219       | 0.543        | 0.662         |

Note: Compiled by the authors.

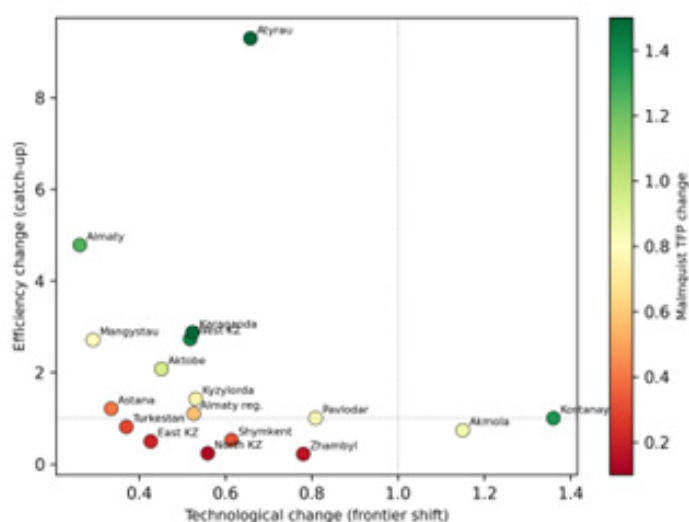


Figure 1 – Malmquist decomposition: efficiency change vs. technological change, 2014–16 to 2022–24 (colour = TFP change)

Note: Compiled by the authors based on data from the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan and the authors' own calculations.

This finding reframes the resource-scale result from a static to a dynamic perspective: it is not merely that R&D scale fails to predict activity levels cross-sectionally (table 1), but that, at the aggregate level, the technological possibilities associated with a given level of R&D input have themselves deteriorated over the observation window: in our estimates the frontier shift is the dominant source of the aggregate TFP decline, and the regions with the sharpest technological regress are the resource-oriented ones. For Smart Specialisation policy, this is a materially different diagnosis than a pure efficiency problem: reallocating existing resources more efficiently within a contracting frontier has a hard ceiling, whereas the national policy conversation (and the Quadruple Helix/GovTech instruments intended to support it) has so far emphasised coordination and monitoring, efficiency-side interventions, over frontier-expanding investment (international technology transfer, R&D infrastructure renewal, university-industry research capacity).

Spatial autocorrelation of productivity change

The global Moran's I for log Malmquist TFP change is 0.148 (999-permutation pseudo-p = 0.436): the null of no spatial autocorrelation cannot be rejected, supporting H2. Fig. 2 visualises the schematic geographic distribution of TFP change, showing no discernible spatial clustering of improving versus declining regions. High- and low-TFP-change regions are interspersed rather than forming contiguous blocks. Combined with the earlier finding (in the author's related work) of no significant spatial autocorrelation in innovation-activity levels, this reinforces an institutional, rather than geographic-spillover, account of regional divergence in Kazakhstan: Smart Specialisation and GovTech instruments cannot rely on productivity or activity 'radiating' from leading to neighbouring regions and must instead be designed and monitored region-by-region.

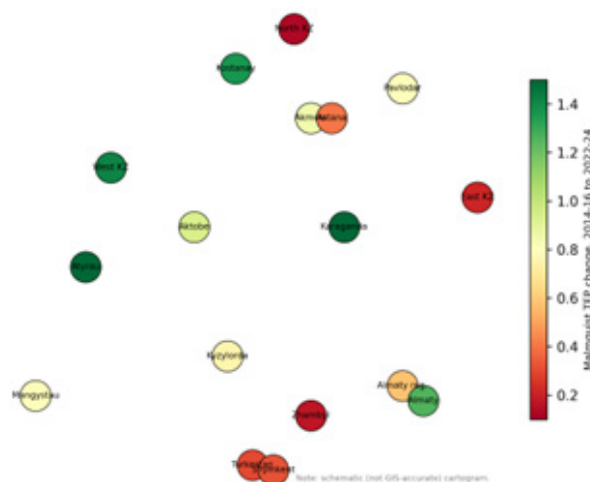


Figure 2 – Schematic cartogram of Malmquist TFP change, 2014–16 to 2022–24

Note: Compiled by the authors based on data from the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan and the authors' own calculations.

#### Factor-analytic adequacy, PCA and regional typology

Before applying any dimension-reduction technique to the five 2024 indicators (GERD, NOEI, patents, IAR, VOIP), sampling adequacy was tested explicitly. Bartlett's test of sphericity is significant ( $\chi^2 = 86.5$ ;  $p < 0.001$ ), but the overall Kaiser-Meyer-Olkin measure is 0.554, below the conventional 0.6 adequacy threshold [24], with VOIP showing particularly poor adequacy ( $KMO = 0.101$ ), consistent with its near-orthogonality to the other four indicators already suggested by the PCA loading pattern below. Exploratory factor analysis is therefore not reported as a substantive result: this is precisely the situation in which the correct methodological choice is to fall back on PCA, which does not require the common-factor-model assumptions underlying EFA and is markedly more robust at  $n = 17$ .

PCA shows the first two components explain 83.5% of variance ( $PC1 = 62.6\%$ ;  $PC2 = 20.9\%$ );  $PC1$  loads positively on GERD, NOEI, patents and IAR (an input/adoption-scale factor) while  $PC2$  loads almost exclusively on VOIP (0.897, an orthogonal market-conversion factor) - the same structure that explains VOIP's poor KMO score. Ward hierarchical clustering and independent K-means clustering ( $k = 4$ ) agree closely (Adjusted Rand Index = 0.779), yielding a robust typology: a leader (Almaty city); catching-up industrial regions (Astana, Karaganda, Pavlodar, North Kazakhstan, Aktobe, Kyzylorda, Turkestan); resource regions with low innovation diffusion (Atyrau, West Kazakhstan, Mangystau, East Kazakhstan, Almaty region, Zhambyl, Shymkent); and a conversion outlier (Kostanay). This typology maps naturally onto Smart Specialisation archetypes: the leader and catching-up groups are plausible candidates for R&D-intensive specialisation domains, whereas resource regions - which combine substantial GERD with low diffusion and, per Table 3, some of the sharpest technological regress (e.g. North Kazakhstan, Zhambyl) - require a differently designed entrepreneurial discovery process centred on technology transfer from extractive-sector R&D into adjacent civilian applications, an explicit Quadruple Helix coordination task.

Weighting-method comparison (PCA, entropy [26]) shows divergent weight values (Spearman rank correlation between PCA and entropy weights = 0.50,  $p = 0.391$ ). The resulting TOPSIS rankings are nevertheless highly robust to the choice of weighting scheme (Spearman rank correlation between the PCA-weighted and entropy-weighted rankings = 0.909,  $p < 0.001$ ) – methodologically reassuring for any GovTech platform intended to operationalise a composite regional index using more than one weighting convention.

Static (2024) DEA decomposition into CCR (constant returns) and BCC (variable returns) efficiency again illustrates the scale-versus-management distinction relevant to targeted Smart Specialisation support: West Kazakhstan is purely technically efficient (BCC = 1.0) yet scores very low on CCR (0.269) purely due to scale inefficiency, implying that infrastructure consolidation, not managerial reform, is the appropriate intervention, whereas Aktobe’s low efficiency under both specifications (BCC = 0.246; CCR = 0.148) points to genuine resource-management weaknesses better addressed through Quadruple Helix coordination and GovTech-enabled monitoring.

Machine-learning attribution of cross-sectional DEA efficiency

Table 4 reports leave-one-out cross-validated performance of three tree-ensemble learners predicting 2022–2024 average DEA (CCR) efficiency from structural features (log GERD, log NOEI, log VOIP, IAR, resource- and agglomeration-region dummies). Given  $n = 17$ , these results are exploratory rather than production-grade, but all three models achieve moderate out-of-sample fit, with gradient boosting performing best.

Table 4 – Leave-one-out cross-validated performance predicting DEA efficiency ( $N = 17$ )

| Model                                   | LOO R2 | RMSE  | MAE   |
|-----------------------------------------|--------|-------|-------|
| Random Forest                           | 0.434  | 0.223 | 0.161 |
| Gradient boosting<br>(XGBoost analogue) | 0.540  | 0.201 | 0.152 |
| CatBoost                                | 0.444  | 0.221 | 0.154 |

Note: Compiled by the authors.

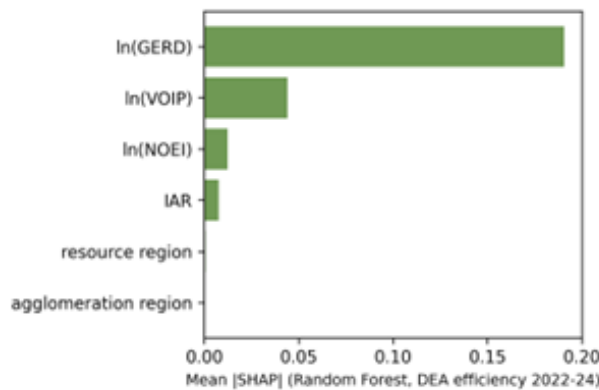


Figure 3 – SHAP feature importance for DEA efficiency (Random Forest, full-sample fit)

Note: Compiled by the authors based on data from the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan and the authors’ own calculations.

SHAP and native feature-importance rankings agree across all three models (Random Forest, gradient boosting and CatBoost all rank log(GERD) first, log(VOIP) second): log(GERD) alone accounts for 77–80% of attributed importance. This finding requires a careful, non-mechanical reading: because GERD is the sole DEA input in this specification, efficiency scores are, by construction, inversely related to input scale for a given output level, so a strong GERD attribution partly reflects DEA’s well-documented tendency to favour small-scale decision-making units [16] rather than

revealing an independent causal driver. This caveat is itself a useful, auditable finding for an AI-Governance-compliant decision-support tool: an explainability layer that surfaces this mechanical relationship (rather than presenting the efficiency score as a black-box merit ranking) is precisely what distinguishes responsible from irresponsible use of ML-based regional scoring in public policy [5, 7].

#### National productivity trend

The national IAR series (11 annual observations, augmented Dickey-Fuller statistic -2.778,  $p = 0.062$ ) is best modelled by ARIMA(1,1,0) (AIC = 24.45). The AR(1) coefficient is insignificant ( $b = 0.244$ ,  $p = 0.594$ ), so the series is essentially a random walk with drift, and the 2025-2027 point forecast stabilises around 11.95-11.96% with a rapidly widening confidence interval. Given the series' short length, this is reported as an illustrative extrapolation of the recent trend rather than an operational forecast, consistent with the more informative dynamic evidence from the Malmquist decomposition above.

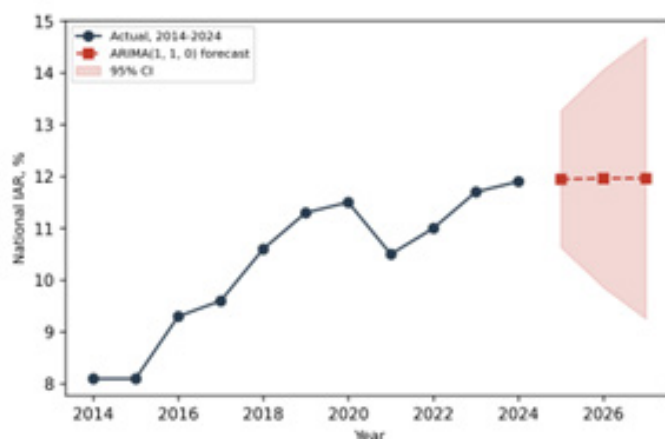


Figure 4 – National innovation-activity trend and ARIMA(1,1,0) extrapolation, 2025–2027

Note: Compiled by the authors based on data from the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan and the authors' own calculations.

#### Critical discussion: implications for Smart Specialisation, Quadruple Helix and GovTech/AI Governance

The central empirical contribution of this study – that Kazakhstan's regional innovation-productivity decline over 2014–2024 is a technological-regress, not an efficiency, problem – carries direct implications for the sequencing of Smart Specialisation, Quadruple Helix and GovTech/AI Governance instruments that the existing Kazakhstani literature has not drawn out. First, Smart Specialisation's entrepreneurial discovery process is designed to reallocate existing resources toward higher-return domains within a given technological frontier [1, 2]. It is not designed to expand a contracting frontier. Applied uncritically in Kazakhstan, S3 risks becoming an efficiency-reallocation exercise that cannot address the dominant technological-regress component identified here, unless it is explicitly paired with frontier-expanding investment – international technology transfer, renewed R&D infrastructure, and deeper integration into global value chains, as documented for successful catch-up economies elsewhere [8, 12]. Second, the Quadruple Helix's promise is precisely to mobilise underused civil-society and industry linkages to accelerate diffusion once a technology exists [3]. The positive, widespread efficiency-catch-up finding here (9 of 17 regions improving) is consistent with Quadruple Helix-style coordination already delivering some genuine value, even as the shrinking frontier limits how much further catch-up alone can achieve. Third, GovTech and AI Governance frameworks are usually framed as monitoring and coordination tools [4, 5, 9]. This study's evidence suggests their highest-value use in Kazakhstan's current context may be diagnostic rather than purely operational – an AI-Governance-compliant decision-support layer (of the kind outlined in the author's related architectural work) that continuously distinguishes efficiency-catch-up regions from frontier-

regress regions would let policymakers target instruments correctly instead of applying a uniform coordination-improvement template nationally.

These findings should be read against a wider international literature. Balland et al. [8] show that European regions specialising in technologically related domains achieve more persistent productivity growth than those chasing generic ‘high-tech’ priorities irrespective of existing capability – a lesson directly applicable to Kazakhstan’s resource regions, whose comparative advantage in extractive-sector engineering has not yet been systematically converted into an S3 domain. The innovation-paradox literature on resource-dependent economies [13, 14, 15] anticipated exactly the kind of investment-output decoupling this study documents dynamically. What this study adds is the decomposition showing that the problem is frontier-side rather than allocation-side, a distinction that literature using only cross-sectional productivity ratios could not make. The absence of significant spatial autocorrelation in both innovation-activity levels and productivity change also contrasts with the positive regional spillovers routinely documented for EU NUTS-2 regions [2], where dense, spatially localised firm and research linkages support neighbourhood diffusion; Kazakhstan’s more centralised, administratively coordinated innovation system appears to lack this channel, reinforcing the case for region-specific rather than spillover-based policy design.

The scientific contribution of this study is fourfold. First, it is the first application of Malmquist-DEA productivity decomposition to Kazakhstan’s regional innovation systems, distinguishing technological change from efficiency catch-up – a distinction absent from the descriptive and cross-sectional literature to date. Second, it demonstrates, through an explicit KMO/Bartlett adequacy test, that exploratory factor analysis is not statistically justified for this indicator set and sample size, and documents PCA as the methodologically correct alternative – a transparent, falsifiable methodological choice rather than a default one. Third, it provides a comparative, cross-validated machine-learning attribution of DEA efficiency (Random Forest, gradient boosting, CatBoost with SHAP), explicitly flagging the mechanical DEA-scale relationship behind the dominant feature, a level of interpretive caution consistent with AI Governance requirements for explainable public-sector algorithms. Fourth, it translates these quantitative findings into an explicit sequencing recommendation for Smart Specialisation, Quadruple Helix and GovTech/AI Governance instruments, an integration not previously made in the Kazakhstani literature.

Limitations must be stated explicitly. The Malmquist specification uses a single input (GERD) because patent data are unavailable for 2014, constraining the output set to NOEI and VOIP; extending the decomposition to a fuller input-output set requires future data collection on regional patenting over time. The quadratic diminishing-returns test at the activity-level regression is statistically inconclusive (Table 2), and should be read as a complementary, not confirmatory, check alongside the more powerful nonparametric Malmquist result. The cross-sectional machine-learning models operate on  $n = 17$  and should be read as an exploratory attribution exercise, not a validated predictive tool. The spatial weights matrix reflects administrative contiguity only, not functional economic proximity; and, as in related work, indicators are measured in nominal prices. Future research should extend the Malmquist panel as patent time series become available, test alternative spatial-weight specifications (transport or trade-flow based), and empirically operationalise the AI-Governance-compliant decision-support layer implied by this study’s diagnostic distinction between technological-regress and efficiency-catch-up regions.

## Conclusion

This study decomposed total factor productivity change in the innovation systems of 17 Kazakhstani regions (2014–2024, 187 panel observations) into efficiency-catch-up and technological-change components using Malmquist-DEA, complemented by panel regression, spatial autocorrelation testing, PCA-based typology and machine-learning attribution of efficiency. All three hypotheses are supported. H1 is confirmed: national geometric-mean TFP change over 2014–2016 to 2022–2024 is 0.662, driven predominantly by technological regress (0.543) and only partly offset by positive efficiency catch-up (1.219) – a frontier problem, not primarily an allocation problem. H2 is confirmed: neither innovation-activity levels nor productivity change show significant spatial autocorrelation (Moran’s  $I = 0.148$ ,  $p = 0.436$ , for TFP change), indicating an institutional rather than geographic

diffusion mechanism. H3 is confirmed: three independent machine-learning models (Random Forest, gradient boosting, CatBoost) attribute cross-sectional efficiency variation with moderate, cross-validated confidence, and SHAP-based interpretation surfaces both a substantive driver and an important methodological caveat about DEA's scale sensitivity – exactly the kind of transparent attribution an AI-Governance-compliant decision-support tool must provide.

Practical recommendations follow directly. First, Kazakhstan's Smart Specialisation priority-setting should explicitly distinguish regions facing technological regress from those facing efficiency shortfalls, using a Malmquist-type decomposition computed on a rolling basis, and should pair entrepreneurial-discovery exercises with dedicated frontier-expanding investment (international technology transfer, R&D infrastructure) in regress-dominated regions rather than efficiency-oriented coordination reforms alone. Second, Quadruple Helix coordination mechanisms should be prioritised in regions already showing positive efficiency catch-up, where further orchestration of government-industry-academia-society linkages can still yield returns, while in frontier-regress regions Quadruple Helix efforts should be explicitly linked to technology-transfer partnerships rather than purely domestic coordination. Third, any GovTech platform or AI Governance-compliant decision-support tool built to monitor regional innovation policy should report both DEA efficiency and Malmquist productivity change, together with SHAP-style attribution and an explicit statement of each method's known biases (e.g. DEA's small-scale bias), rather than a single composite score. Fourth, given the absence of spatial spillovers, resource allocation across regions should not assume automatic diffusion from leading regions and should instead be calibrated region-by-region.

Future research directions include extending the Malmquist decomposition to a fuller multi-output specification once regional patent time series become available; testing alternative, functional (rather than purely administrative) spatial-weight matrices; validating the machine-learning attribution of efficiency on firm-level rather than regional-aggregate data; and empirically piloting the AI-Governance-compliant, dual efficiency/productivity decision-support layer proposed here within an actual regional GovTech platform.

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## **ҚАЗАҚСТАН ӨНІРЛЕРІНІҢ ӨНІМДІЛІК ӨСУІНІҢ ДЕКОМПОЗИЦИЯСЫ: ТЕХНОЛОГИЯЛЫҚ ПРОГРЕСС ЖӘНЕ РЕСУРСТАРДЫ ПАЙДАЛАНУ ТИІМДІЛІГІ**

### **Андатпа**

Қазақстанның өңірлік инновациялық саясаты (соның ішінде ақылды мамандану және төрттік спираль тәсілдері) негізінен статикалық көрсеткіштерге сүйенеді, ал ресурстарды нәтижеге айналдырудың динамикасына технологиялық жылжу мен тиімділікке жетудің үлесі бөлек ескерілмейді. Зерттеудің мақсаты – Қазақстан өңірлерінің инновациялық жүйелеріндегі жиынтық факторлық өнімділіктің (TFP) өзгеруін Malmquist-DEA негізінде тиімділікке жету және технологиялық жылжу компоненттеріне жіктеу, сондай-ақ бұл өзгерістің кеңістіктік және құрылымдық детерминанттарын анықтау болып табылады. Гипотеза: 2014–2024 жж. аралығында өңірлік инновациялық өнімділіктің орташа төмендеуі негізінен технологиялық шегініспен түсіндіріледі, ал бұл процесс географиялық емес, институционалдық сипатта. Қазақстан Республикасы Ұлттық статистика бюросының 2014–2024 жж. 17 өңір бойынша панельдік деректері (187 бақылау) пайдаланылды, оған панельдік регрессия, Malmquist-DEA ыдырауы, кеңістіктік автокорреляцияны талдау, негізгі компоненттер әдісі мен кластерлік талдау, энтропиялық өлшеу және TOPSIS, сондай-ақ түсіндірілетін машиналық оқыту (Random Forest, градиенттік бустинг, SHAP көмегімен CatBoost) кіреді. Нәтижелер бойынша, 2014–2016 және 2022–2024 жж. аралығында геометриялық орта TFP өзгерісі 0,662-ні құрады, бұл негізінен технологиялық шегіністен (0,543) туындайды, ал тиімділікке жету оң болды (1,219). Өнімділік өзгерісінің ғаламдық кеңістіктік автокорреляциясы анықталмады (Моран индексі = 0,148;  $p = 0,436$ ), бұл диффузияның институционалдық сипатын растайды. Нәтижелер Қазақстанның ақылды мамандану және GovTech/AI Governance саясатын тиімділікке емес, технологиялық жаңғыртуға бағыттау қажеттігін көрсетеді, бұл мемлекеттік инновациялық қолдау бағдарламалары мен даму институттарының тиімділігін жыл сайын бақылау және салыстырмалы бағалау үшін маңызды.

**Тірек сөздер:** өңірлік инновациялық жүйе, Malmquist индексі, DEA, ақылды мамандану, төрттік спираль, жасанды интеллект басқармасы, машиналық оқыту.

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## **ДЕКОМПОЗИЦИЯ РОСТА ПРОИЗВОДИТЕЛЬНОСТИ РЕГИОНОВ КАЗАХСТАНА: ТЕХНОЛОГИЧЕСКИЙ ПРОГРЕСС И ЭФФЕКТИВНОСТЬ ИСПОЛЬЗОВАНИЯ РЕСУРСОВ**

### **Аннотация**

Региональная инновационная политика Казахстана (включая подходы умной специализации и четверной спирали) опирается преимущественно на статические показатели, тогда как вклад технологического сдвига и догоняющей эффективности в динамику конвертации ресурсов в результат остается неисследованным отдельно. Цель исследования – разложить изменение совокупной факторной производительности (TFP) инновационных систем регионов Казахстана на компоненты догоняющей эффективности и технологического сдвига методом Malmquist-DEA, а также выявить пространственные и структурные детерминанты этого изменения. Гипотеза: среднее снижение региональной инновационной производительности за 2014–2024 гг. объясняется преимущественно технологическим регрессом (сжатием границы производственных возможностей), а сам процесс носит не географический, а институциональный характер. Использована панель официальных данных Бюро национальной статистики РК за 2014–2024 гг. по 17 регионам (187 наблюдений), включающая панельную регрессию, декомпозицию Malmquist-DEA, анализ пространственной автокорреляции, метод главных компонент и кластерный анализ, энтропийное взвешивание и TOPSIS, а также объяснимое машинное обучение (Random Forest, градиентный бустинг, CatBoost с SHAP). Результаты показывают, что геометрическое среднее изменение TFP за 2014–2016 и 2022–2024 гг. составило 0,662, что обусловлено преимущественно технологическим регрессом (0,543) при положительной догоняющей эффективности (1,219). Глобальная пространственная автокорреляция изменения производительности не выявлена (индекс Морана = 0,148;  $p = 0,436$ ), что подтверждает институциональный характер диффузии. Результаты указывают на необходимость переориентации политики умной специализации и GovTech/AI Governance в Казахстане на технологическое обновление, а не только на повышение эффективности, что имеет практическое значение для мониторинга государственных программ поддержки инноваций и институтов развития.

**Ключевые слова:** региональная инновационная система, индекс Малмквиста, DEA, умная специализация, четверная спираль, управление искусственным интеллектом, машинное обучение.

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