

**ADAPTING HIGHER EDUCATION MANAGEMENT TO REGIONAL
LABOR-MARKET CONDITIONS IN UZBEKISTAN: EVIDENCE FROM A TWO-
WAY FIXED-EFFECTS PANEL, 2011–2025**

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Abstract. This study examines whether regional labor-market conditions in Uzbekistan can provide useful context for higher education management. Three official datasets were merged into a balanced panel of 14 regions for 2011–2025, yielding 210 region-year observations. The regional employment rate is modeled against lagged non-state employment intensity, defined as non-state employment relative to the economically active population, and annual growth in the economically active population. A two-way fixed-effects model controls for persistent regional differences and common annual shocks; standard errors are clustered by region with a finite-sample correction. The coefficients on lagged non-state employment intensity ($\beta = 0.652$, $SE = 0.341$, $p = 0.078$) and labor-force growth ($\beta = 0.179$, $SE = 0.084$, $p = 0.054$) are positive but do not reach the 5% significance level. The focal regressors are jointly significant only at 10% ($F(2,13) = 2.991$, $p = 0.085$). Diagnostics reveal heteroskedasticity, serial correlation, and functional-form limitations, so the estimates are interpreted as conditional associations rather than causal effects. Regional labor-market indicators can inform curriculum review, employer consultation, and graduate tracking, but they cannot substitute for program-level evidence.

Keywords: higher education management; regional labor market; non-state employment intensity; employment rate; panel data; fixed effects.

**АДАПТАЦИЯ УПРАВЛЕНИЯ ВЫСШИМ ОБРАЗОВАНИЕМ К
РЕГИОНАЛЬНЫМ УСЛОВИЯМ РЫНКА ТРУДА В УЗБЕКИСТАНЕ:
ДВУСТОРОННИЙ ПАНЕЛЬНЫЙ АНАЛИЗ С ФИКСИРОВАННЫМИ
ЭФФЕКТАМИ, 2011–2025 гг.**

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Аннотация. В статье оценивается, в какой мере региональные показатели рынка труда Узбекистана могут использоваться в управлении высшим образованием. Три официальных массива данных объединены в сбалансированную панель по 14 регионам за 2011–2025 гг., включающую 210 наблюдений «регион–год». Уровень занятости объясняется лагированной интенсивностью занятости в негосударственном секторе, рассчитанной относительно экономически активного населения, и годовым ростом экономически активного населения. Двусторонняя модель с фиксированными эффектами учитывает устойчивые региональные различия и общие годовые шоки; стандартные ошибки кластеризованы по регионам с поправкой на малое число кластеров. Коэффициенты при лагированной интенсивности негосударственной занятости ($\beta = 0,652$; $SE = 0,341$; $p = 0,078$) и росте рабочей силы ($\beta = 0,179$; $SE = 0,084$; $p = 0,054$) положительны, но не достигают 5%-ного уровня значимости. Диагностика выявляет гетероскедастичность, серийную корреляцию и ограничения функциональной формы, поэтому результаты трактуются как условные взаимосвязи. Региональные индикаторы полезны для пересмотра программ, консультаций с работодателями и мониторинга выпускников, но не заменяют данные на уровне образовательных программ.

Ключевые слова: управление высшим образованием; региональный рынок труда; интенсивность занятости в негосударственном секторе; уровень занятости; панельные данные; фиксированные эффекты.

**O‘ZBEKISTONDA OLIY TA’LIM BOSHQARUVINI HUDUDIIY MEHNAT
BOZORI SHAROITLARIGA MOSLASHTIRISH: 2011–2025-YILLAR UCHUN
IKKI YO‘NALISHLI FIKSIRLANGAN EFFEKTLAR PANEL TAHLILI**

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Annotatsiya. Ushbu tadqiqot O‘zbekiston hududlaridagi mehnat bozori ko‘rsatkichlaridan oliy ta’lim boshqaruvida qay darajada foydalanish mumkinligini baholaydi. Uchta rasmiy ma’lumotlar to‘plami 2011–2025-yillar bo‘yicha 14 hududni qamrab olgan 210 ta “hudud–yil” kuzatuvli muvozanatlashgan panelga birlashtirildi. Hududiy bandlik darajasi bir yilga kechiktirilgan nodavlat sektordagi bandlik intensivligi — nodavlat bandlikning iqtisodiy faol aholiga nisbati — hamda iqtisodiy faol aholi sonining yillik o‘sishi bilan izohlandi. Ikki yo‘nalishli fiksirlangan effektlar modeli doimiy hududiy farqlar va umumiy yillik shoklarni nazorat qiladi; standart xatolar hududlar bo‘yicha klasterlandi. Nodavlat bandlik intensivligi ($\beta = 0,652$; $SE = 0,341$; $p = 0,078$) va mehnat resurslari o‘sishi ($\beta = 0,179$; $SE = 0,084$; $p = 0,054$) koeffitsiyentlari ijobiy, biroq 5 foizlik ahamiyatlilik darajasiga yetmadi. Diagnostika geteroskedastiklik, ketma-ket korrelyatsiya va funksional shakl cheklovlarini ko‘rsatdi; shu sababli natijalar sababiy ta’sir emas, shartli bog‘liqlik sifatida talqin qilinadi. Hududiy ko‘rsatkichlar o‘quv dasturlarini ko‘rib chiqish, ish beruvchilar bilan maslahatlashuv va bitiruvchilar monitoringi uchun foydali, ammo dastur darajasidagi dalillarni almashtirmaydi.

Kalit soʻzlar: oliy taʼlim boshqaruvi; hududiy mehnat bozori; nodavlat sektordagi bandlik intensivligi; bandlik darajasi; panel maʼlumotlar; fiksirlangan effektlar.

1. Introduction

Higher education institutions are expected to respond to changes in employment, technology, and employer demand while preserving academic quality. Yet the relationship between higher education and employment is indirect: growth in enrollment does not guarantee productive work, and an improving employment rate does not reveal which occupations, qualifications, or fields of study are needed. Labor-market statistics are therefore useful as context, not as automatic rules for changing curricula or enrollment.

This distinction is especially relevant in Uzbekistan, where regions differ in industrial structure, urbanization, migration, population growth, and employment opportunities. National averages can conceal these differences. International evidence also points to the territorial dimension of higher education: Valero and Van Reenen (2019), using data for roughly 1,500 regions in 78 countries, link university expansion to subsequent regional growth through human-capital and innovation channels. Regional evidence can therefore improve institutional planning, provided that its limits are stated clearly.

Previous work has addressed graduate employment, university–industry relations, autonomy, competition, performance measurement, and graduate competencies (Brennan & Teichler, 2008; Etzkowitz & Leydesdorff, 2000; Yuldashev, 2023, 2024a, 2024b, 2024c, 2024d, 2025a, 2025b). However, longitudinal regional evidence for Uzbekistan remains limited. The present study replaces an earlier 16-observation national time series with a balanced panel of 14 regions. It asks whether current regional employment rates are associated with the previous year’s non-state employment intensity and with annual growth in the economically active population, and how such evidence can be used in higher education management without being mistaken for a direct measure of university performance.

2. Literature Review and Hypotheses

2.1 Higher education, employment, and regional development

Brennan and Teichler (2008) treat graduate employment as a joint outcome of individual characteristics, higher education systems, and the wider economy. Etzkowitz and Leydesdorff (2000) explain how universities, industry, and government interact in innovation systems, while Perkmann et al. (2013) show that university–industry engagement extends beyond patents to collaborative research, consulting, contract work, and informal exchange. Together, these studies support structured employer involvement, but not mechanical adjustment of academic programs to short-term labor-market fluctuations. Valero and Van Reenen (2019) add a regional perspective by showing that universities may also shape local development through human-capital formation and knowledge spillovers.

2.2 Adaptive management and performance evidence

Research on Uzbekistan emphasizes the organizational conditions needed for adaptation. Institutional autonomy may improve responsiveness only when it is supported by reliable information and accountability (Yuldashev, 2024b), while competition can encourage quality improvement but may also reward expansion and promotion when performance evidence is weak (Yuldashev, 2024c). Internal capacity remains important: teacher–student proportionality affects educational processes (Yuldashev, 2023), and integrated indicator systems can support strategic monitoring if the measures are conceptually relevant and comparable (Yuldashev, 2024a, 2024d). Weighted principal component analysis offers one way to summarize institutional performance (Yuldashev, 2025b), whereas graduate competency profiles provide evidence closer to curriculum decisions than aggregate employment data (Yuldashev, 2025a).

2.3 Research gap and hypotheses

Aggregate employment indicators do not measure skills mismatch. Montt (2017) distinguishes qualification mismatch from field-of-study mismatch and shows that both depend on the supply of graduates and occupational demand. The available Uzbek datasets

contain neither occupations nor qualifications, so this study estimates regional labor-market associations rather than graduate mismatch or university effectiveness. Two hypotheses are tested: H1: $\beta_1 > 0$, meaning that higher lagged non-state employment intensity is associated with a higher current employment rate; and H2: $\beta_2 < 0$, meaning that faster growth in the economically active population lowers the employment rate when job creation does not keep pace. The second sign is theoretically ambiguous because labor-force growth may accompany economic expansion.

3. Methodology

3.1 Data and research design

Three datasets from the Statistics Agency under the President of the Republic of Uzbekistan were merged by region and year: economically active population, employment rate, and employment in the non-state sector (Statistics Agency, n.d.-a, n.d.-b, n.d.-c). The national aggregate was excluded because it duplicates the underlying regional observations. District and city records were also excluded because comparable district-level data were unavailable for the other variables. The balanced panel contains 14 regions observed from 2011 to 2025, or 210 region-year observations after introducing a one-year lag. No duplicated region-year records or missing values were found in the estimation sample.

The ownership indicator covers the broad non-state sector rather than private employment alone. Comparable regional series for public-sector employment and higher-education employment were not available in the uploaded official datasets and could not be derived without introducing inconsistent definitions. This limitation is retained explicitly rather than replacing observed data with unverified estimates.

3.2 Variables and model

The dependent variable is the regional employment rate (ER), measured as employed persons divided by the permanent working-age population. Non-state employment and the economically active population (EAP) are reported in thousands of persons. Using both raw counts in the same regression is inappropriate because they mainly capture regional size and

have a correlation of 0.992. Non-state employment is therefore converted into an intensity measure:

$$NSEI_{it} = (NSE_{it} / EAP_{it}) \times 100 \quad 1)$$

NSEI is not the non-state share of total employment; it is non-state employment relative to the economically active population. Annual labor-force growth is measured as:

$$gEAP_{it} = 100[\ln(EAP_{it}) - \ln(EAP_{i,t-1})] \quad (2)$$

The preferred two-way fixed-effects specification is:

$$ER_{it} = \alpha_i + \lambda_t + \beta_1 NSEI_{i,t-1} + \beta_2 gEAP_{it} + \varepsilon_{it} \quad (3)$$

Region effects (α_i) absorb time-invariant territorial characteristics, and year effects (λ_t) absorb national shocks and common trends. Lagging NSEI improves temporal ordering but does not eliminate endogeneity or the accounting links among labor-market variables.

Table 1. Variable definitions and measurement

Variable	Definition and unit	Expected sign	Interpretation and source
ER_{it}	Employed population / permanent working-age population $\times 100$; percent	Dependent variable	Regional employment outcome; official employment-rate dataset
$NSEI_{i,t-1}$	Previous-year non-state employment / EAP $\times 100$; percent	Positive	Prior non-state employment intensity; constructed from non-state-employment and EAP datasets
$gEAP_{it}$	$100[\ln(EAP_{it}) - \ln(EAP_{i,t-1})]$; annual log percentage change	Initially negative; empirically ambiguous	Annual change in regional labor-force supply; constructed from EAP data
$\alpha_i; \lambda_t$	Region and year indicator controls	Not interpreted	Time-invariant regional characteristics and common annual shocks

Note. NSEI denotes non-state employment intensity; EAP denotes the economically active population.

3.3 Estimation and diagnostic strategy

Pooled OLS and region fixed effects are reported as benchmarks, followed by the preferred two-way fixed-effects model. Fixed effects are appropriate because persistent regional characteristics are likely to correlate with labor-market structure; the Mundlak test provides an additional check. Standard errors are clustered by region with a finite-sample correction for 14 clusters. Inference therefore concerns conditional associations, not causal effects. The procedure follows standard panel-data principles (Wooldridge, 2019).

Diagnostics cover multicollinearity, the joint relevance of region and year effects, correlated regional effects, heteroskedasticity, serial correlation, cross-sectional dependence, functional form, and residual normality. Robustness checks use a contemporaneous NSEI specification, first differences, leave-one-region-out estimation, and selected year exclusions. Panel stationarity tests are treated as sensitivity evidence because the time dimension is short.

4. Results

4.1 Descriptive statistics, correlation, and multicollinearity

Table 2. Descriptive statistics for the estimation sample, 2011–2025

Variable	N	Mean	Median	Min.	Max.	Std. dev.	CV (%)
Employment rate (ER)	210	67.716	67.000	56.000	86.900	5.893	8.702
Lagged non-state employment intensity (NSEI _{t-1})	210	74.977	76.101	52.370	82.032	5.370	7.162
Growth in economically active population (gEAP)	210	1.643	1.624	−3.293	12.370	2.191	133.365

Note. CV is the sample standard deviation divided by the absolute mean. For gEAP, the CV has limited substantive meaning because the series includes negative values and has a mean close to zero.

The mean employment rate is 67.716%, with substantial variation across regions and years. Lagged NSEI averages 74.977%, but this figure must not be read as a share of total employment. The economically active population grows by 1.643% per year on average and includes both contractions and rapid expansions.

Table 3. Pearson correlation matrix

Variable	ER	Lagged NSEI	gEAP
ER	1.000	-0.189	-0.021
Lagged NSEI	-0.189	1.000	0.193
gEAP	-0.021	0.193	1.000

Note. Pooled correlations combine between-region differences and within-region changes; they are descriptive and should not be read as fixed-effects estimates.

The pooled relationship between ER and lagged NSEI is negative ($r = -0.189$), whereas the within-region coefficient becomes positive after region and year effects are controlled. ER and gEAP are almost uncorrelated in the pooled data. The correlation between the transformed regressors is only 0.193.

Table 4. Variance inflation factors and tolerance statistics

Specification	Variable	VIF	Tolerance
Original raw-count model	Non-state employment	64.507	0.016
Original raw-count model	Economically active population	64.507	0.016
Transformed pooled model	Lagged NSEI	1.039	0.963
Transformed pooled model	gEAP	1.039	0.963
Transformed two-way-within model	Lagged NSEI	1.032	0.969

Specification	Variable	VIF	Tolerance
Transformed two-way-within model	gEAP	1.032	0.969

Note. The original raw regressors have a pairwise correlation of 0.992. Transformation reduces VIF values from 64.507 to about 1.03.

The raw-count specification is not defensible because both variables mainly capture regional scale. The transformed model removes this severe multicollinearity.

4.2 Panel regression estimates

Table 5. Panel regression estimates: dependent variable is regional employment rate

Variable/statistic	Pooled OLS	Region FE	Two-way FE	Contemporaneous NSEI
Lagged NSEI coefficient	−0.210	0.405	0.652	—
Clustered SE	0.226	0.118	0.341	—
p value	0.368	0.005	0.078	—
Contemporaneous NSEI coefficient	—	—	—	0.536
Clustered SE	—	—	—	0.374
p value	—	—	—	0.175
gEAP coefficient	0.044	0.184	0.179	0.111
Clustered SE	0.259	0.099	0.084	0.091
p value	0.869	0.085	0.054	0.246
Observations	210	210	210	210
Region effects	No	Yes	Yes	Yes
Year effects	No	No	Yes	Yes

Variable/statistic	Pooled OLS	Region FE	Two-way FE	Contemporaneous NSEI
Overall R ²	0.036	0.848	0.878	0.870
Adjusted R ²	0.026	0.836	0.858	0.849
Within R ²	—	—	0.213	—
Classical model F	3.843	72.196	44.576	41.592

Note. Standard errors are clustered by region with a finite-sample correction. Two-sided p values use 13 cluster degrees of freedom. Exact p values are reported instead of significance stars.

The pooled model has little explanatory power. Introducing region effects changes the sign of NSEI from negative to positive, indicating that the pooled correlation mainly reflects persistent differences between regions. In the preferred two-way model, lagged NSEI has a coefficient of 0.652 (SE = 0.341, $p = 0.078$). A one-percentage-point increase in prior non-state employment intensity is associated with a 0.652-percentage-point higher employment rate, but the approximate 95% confidence interval (−0.084 to 1.388) includes zero. H1 therefore receives only weak support at 10%.

The gEAP coefficient is 0.179 (SE = 0.084, $p = 0.054$), with an approximate 95% interval from −0.003 to 0.360. Its positive sign contradicts H2. The focal regressors are jointly significant at 10% but not at 5% (cluster-robust Wald $F(2,13) = 2.991$, $p = 0.085$). The overall R² of 0.878 is driven partly by region and year effects; the within R² of 0.213 is more informative about variation after those effects are removed. The contemporaneous specification produces positive but statistically insignificant coefficients, so the lagged result should be treated as suggestive.

4.3 Model selection, diagnostics, and robustness

Table 6. Model-selection and diagnostic tests

Test	Statistic	p value	Interpretation
Joint significance of region effects	F = 79.786	<0.001	Region effects are required
Joint significance of year effects	F = 3.125	<0.001	Year effects are required
Mundlak correlated-effects test	F = 8.202	0.005	Supports fixed effects
Koenker–Bassett heteroskedasticity test	LM = 141.707	<0.001	Heteroskedasticity is present
Brown–Forsythe residual-variance test	F = 12.633	<0.001	Residual variances differ across regions
Wooldridge-type serial-correlation test	F = 283.470	<0.001	First-order serial correlation is present
Residual AR(1) auxiliary test	F = 25.743	<0.001	Strong positive residual persistence
Pesaran cross-sectional dependence test	CD = -1.579	0.114	Cross-sectional independence is not rejected
Ramsey RESET	F = 22.365	<0.001	Simple linear functional form is rejected
Jarque–Bera residual-normality test	JB = 4.453	0.108	Residual normality is not rejected
Panel Durbin–Watson (supplementary)	0.255	—	Consistent with positive serial correlation

Note. Formal panel serial-correlation tests are preferred to Durbin–Watson. Clustered covariance estimates improve inference under heteroskedasticity and within-region dependence but do not repair functional-form misspecification.

Joint tests support the two-way specification, and the Mundlak result indicates correlation between the regressors and unobserved regional effects. Heteroskedasticity and

strong serial correlation justify clustered inference. Cross-sectional independence and residual normality are not rejected, but RESET rejects the simple linear conditional mean. The latter may reflect omitted time-varying variables, nonlinearities, or dynamics that cannot be identified with the three available datasets.

In first differences, annual non-state-employment growth is not associated with the change in employment rate ($\beta = 0.010$, $SE = 0.012$, $p = 0.392$), while gEAP remains positive ($\beta = 0.560$, $SE = 0.034$, $p < 0.001$). Because these variables are linked through labor-market accounting, the result is not causal. Leave-one-region-out estimates preserve positive signs: the lagged NSEI coefficient ranges from about 0.498 to 1.178, and the gEAP coefficient from 0.123 to 0.237. Magnitudes and p values change, showing directional stability but limited precision with 14 clusters.

5. Discussion and Implications

5.1 Interpretation

The regional panel changes the interpretation of the earlier national model. Once regional heterogeneity, common annual shocks, and raw-count multicollinearity are addressed, growth in the economically active population is not negatively related to employment. H2 is rejected. The positive lagged NSEI coefficient is compatible with the idea that an established non-state employment base accompanies favorable labor-market conditions, but reverse causality, omitted factors, and accounting relationships remain plausible. The estimates therefore do not show that non-state-sector expansion causes higher employment.

This cautious interpretation is consistent with Brennan and Teichler (2008), who locate graduate employment within both the education system and the wider economy. It also fits the institutional logic of Etzkowitz and Leydesdorff (2000): a developed non-state economy may provide more opportunities for university–employer interaction, although the model does not observe those mechanisms. Valero and Van Reenen (2019) remind us that the relationship also runs in the opposite direction, because universities may contribute to

regional growth. The present data cannot estimate that contribution or measure mismatch, employability, or curriculum quality.

5.2 Implications for higher education management and policy

Regional labor-market indicators should function as an initial monitoring layer. A university or regional labor-market observatory could combine employment rates, labor-force growth, sectoral employment, vacancies, wages, graduate destinations, and employer-reported competencies. Broad regional changes would trigger program-level investigation rather than immediate changes in quotas or curricula.

Employer advisory boards can help interpret sector-specific trends, but their recommendations should be documented and assessed against academic objectives. Work-integrated learning is useful only when it is designed, supervised, and evaluated. Jackson (2015) shows that workplace participation does not automatically develop employability skills; Costley and Lester (2012) emphasize the educational value of integrating professional practice with university learning, while Garnett (2016) identifies organizational and quality-assurance challenges. Employer involvement should therefore support, not replace, academic responsibility.

Graduate tracking is essential because regional statistics do not show whether graduates find work related to their field or qualification. Internal performance funding should also avoid treating employment as a department's sole responsibility: outcomes depend partly on regional conditions outside the institution. Education authorities and statistical agencies could improve the evidence base by linking enrollment, graduation, occupation, sector, vacancy, wage, migration, and graduate-employment records. Such linkage would make it possible to distinguish public, private, non-state, education-sector, and higher-education employment more accurately.

5.3 Artificial intelligence in labor-market monitoring

The present dataset is too small and narrow to justify a complex artificial-intelligence or machine-learning model. It contains two substantive regressors, 14 regions, and 210 observations; a flexible predictor would be difficult to validate and could overfit. The

diagnostic results nevertheless identify issues that richer future systems should address. Serial correlation suggests dynamics not captured by the static model, while RESET points to possible nonlinearity, interactions, or omitted variables. Any future forecasting exercise should therefore compare advanced methods with transparent econometric baselines and report out-of-sample performance.

AI would be more useful as part of a labor-market information system than as a replacement for the current econometric analysis. Natural-language tools could classify vacancy texts by occupation and competency, link employer surveys with graduate records, flag unusual changes in demand, and update dashboards for academic managers. Deming and Kahn (2018) show that online job advertisements can reveal differences in cognitive, social, managerial, and technical skill requirements across firms and labor markets. Comparable vacancy data for Uzbekistan would add detail that aggregate employment indicators cannot provide, although online advertisements may not represent all occupations or regions.

Such a system would require documented data sources, privacy protection, bias checks, benchmark comparisons, out-of-sample validation, and regular human review. Automated results should not determine admissions quotas, program closure, or curriculum content. Their proper role is to organize evidence, highlight questions for investigation, and support decisions made by academic staff, employers, students, and public authorities.

6. Future Research

Future research should assemble regional data on higher-education employment, graduate output and destinations, occupations, vacancies, wages, sectors, and institutional reforms. A richer design would permit direct mismatch indicators, dynamic models, heterogeneous regional effects, and credible evaluation of specific management changes.

7. Conclusion

This study replaces a 16-observation national time series with a balanced regional panel of 210 observations for 2011–2025. Converting raw employment counts into intensity

and growth measures reduces VIF values from above 64 to about 1.03 and allows persistent regional differences and common annual shocks to be controlled.

Lagged non-state employment intensity and labor-force growth have positive coefficients, but neither is significant at 5%. The results reject the original claim that labor-force growth necessarily lowers employment and do not establish non-state employment as a causal driver. The evidence is informative, but modest.

For higher education management, regional labor-market data are best treated as an early-warning and contextual resource. Curriculum and enrollment decisions require graduate tracking, vacancy and occupation data, employer evidence, and program-level outcomes. Artificial intelligence may help process richer information in the future, but neither automated systems nor aggregate statistics should replace academic judgment.

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