| Impact Factor: | | | | | |
|---|---|---|---|---|---|
| | ISRA (India) = 6.317 | SIS (USA) = 0.912 | ICV (Poland) = 6.630 |
| | ISI (Dubai, UAE) = 1.582 | РИНЦ (Russia) = 0.191 | PIF (India) = 1.940 |
| | GIF (Australia) = 0.564 | ESJI (KZ) = 8.100 | IBI (India) = 4.260 |
| | JIF = 1.500 | SJIF (Morocco) = 6.004 | OAJI (USA) = 0.350 |

SOI: 1.1/TAS DOI: 10.15863/TAS

International Scientific Journal

**Theoretical & Applied Science**

**p-ISSN:** 2308-4944 (print) **e-ISSN:** 2409-0085 (online)

**Year:** 2026 **Issue:** 10 **Volume:** 162

**Received:** 23.10.2026
**Accepted/Published:** 30.10.2026

https://T-Science.org

Issue Article

**Alisher Jurakulovich Siddikov**
Tashkent State University of Economics
Uzbekistan, DSc. Professor
ORCID: https://orcid.org/0009-0007-2890-043X
siddikovalisher1@gmail.com

**Gulchehraxon Ne'matova**
Institute for Advanced Training of Personnel and Statistical Research
PhD Student,
Tashkent, Uzbekistan
ORCID: https://orcid.org/0009-0002-6951-7852
gulchehrahonnematova@gmail.com

# REGIONAL MISALLOCATION OF LABOUR AND HUMAN CAPITAL IN UZBEKISTAN

***Abstract***: *Official statistics in the Republic of Uzbekistan indicate the volume of human capital present in each region, yet they fail to reveal where this human capital is most productive. This article applies the "factor-distortion" framework developed by Lu, Peng, and Fang (2024) to Uzbekistan's 14 regions, utilizing SIAT panel data from 2017-2024 to analyze the distribution of formal-sector employees and those with higher education relative to regional output. The analysis incorporates a wage-differential index adjusted for region-specific labour elasticity, decomposes regional disparities using the Dagum Gini coefficient, and tests for σ- and β-convergence employing wild cluster bootstrap inference.*

*The findings indicate that human capital is over-allocated relative to output in the Southern regions, the Fergana Valley, and the Lower Amudarya region, while it is under-allocated in Tashkent City and the Navoi region. Notably, the observed disparities are significantly smaller when considering formal employment alone, compared to total employment a broader category that encompasses informal workers and labour migrants. The observed disparity in current prices (the SD of the log index rose from 0,32 to 0,49) is primarily a relative price effect: at constant prices, the dispersion for total employment increased to only 0,35 and showed no significant trend for formal or highly educated workers. There is no strong β-convergence, and the magnitude of inter-zonal differences is not statistically significant when compared to random grouping. Reallocating total employment would increase output by 3-16% at the upper bound, while the impact on formal employment would be approximately 1% or less. In the Kashkadarya region, the labour share grew faster than the share of real output. These results caution against interpreting regional productivity gaps as labour market distortions without accounting for prices, informality, and migration.*

***Key words***: *misallocation; human capital; regional labour productivity; Dagum Gini coefficient; convergence; informal employment.*

***Language***: *English*

***Citation***: Siddikov, A.J., & Ne'matova, G. (2026). Regional misallocation of labour and human capital in uzbekistan. *ISJ Theoretical & Applied Science, 10 (162),* 47-55.

***Soi***: https://s-o-i.org/1.1/TAS-10-162-8 ***Doi***: crossref https://dx.doi.org/10.15863/TAS.2026.10.162.8

***Scopus ASCC***: *1804.*

## Introduction

The regions of Uzbekistan exhibit significant disparities in output per worker more so than in almost any other economic indicator. In 2024, the Gross Regional Product (GRP) per employed person in the Navoi region was approximately 3,2 times the national average, and 2,3 times the national average in Tashkent City; conversely, in the Surkhandarya,

Fergana, and Namangan regions, this figure stood at only 0,59-0,66 of the national average. Such disparities raise a critical question for growth and regional policy: are labour and human capital located where they are most productive? If marginal products differ widely across regions, reallocating workers or shifting jobs and capital toward workers could increase national output without requiring additional inputs (Restuccia & Rogerson, 2008; Hsieh & Klenow, 2009).

While official statistics indicate the quantity of labour and human capital present in each region, they do not reveal how these resources are distributed relative to production potential that is, they do not provide measures of productivity. This article specifically measures this indicator. While the approach of Lu, Peng, and Fang (2024) measures the misallocation of human capital in Chinese cities using relative factor-price-distortion coefficients, the present article examines this issue by decomposing regional disparities utilizing the Dagum (1997) Gini coefficient and testing for both σ-convergence and β-convergence. The application is not straightforward: Uzbekistan consists of only 14 first-level administrative units; its employment statistics include labour migrants working abroad; and the output of the Navoi mining region, measured in current prices, is highly sensitive to global metal prices. Each of these characteristics alters the interpretation of the index, and the article addresses them explicitly.

The article explores the following questions: how are total employment, formal employment, and the highly educated workforce distributed in relation to regional output? Do regional disparities primarily exist between or within economic zones? Has the distribution converged between 2017 and 2024? And how significant are the potential gains from reallocation of resources? In the authors' view, the contribution consists of presenting the first regional misallocation indices for Uzbekistan constructed based on official statistics and distinguishing between general, formal, and highly educated labour and demonstrating that the conclusion regarding divergence depends on the price basis used for output; it further shows that, for these same regions, resource allocation and the efficiency of human capital utilization previously assessed using Data Envelopment Analysis (DEA) are distinct phenomena.

***Literature review. Misallocation.*** If disparities in the marginal productivity of factors of production arise across various economic units due to barriers or policy interventions, the total volume of output will fall below the level achievable under an efficient allocation (Restuccia & Rogerson, 2008). According to estimates by Hsieh and Klenow (2009), equalizing marginal productivity across manufacturing firms could increase total factor productivity (TFP) by 30-50 percent in China and by 40-60 percent in India. This approach was subsequently extended to sectors and regions: Aoki (2012) linked sector-specific factor price disparities to total factor productivity (TFP); Chen and Hu (2011) proposed relative distortion coefficients, which have been widely used in studies of Chinese regions; Brandt, Tombe, and Zhu (2013) quantified distortions across Chinese provinces; and Hsieh and Moretti (2019) demonstrated how housing-related constraints in highly productive U.S. cities have dampened overall economic growth. Regarding human capital, Vollrath (2014) found that equalizing returns across various sectors in developing countries leads to a relatively modest increase in total output. Meanwhile, Lu et al. (2024) observed a decline in the misallocation of human capital across Chinese cities; disparities between urban agglomerations serve as a primary factor, with the process exhibiting characteristics of both σ-convergence and β-convergence.

***Measurement caveats.*** Differences in average productivity reflect differences in marginal productivity only if production elasticities are identical across all units; capital intensity and resource rents violate this condition (Restuccia & Rogerson, 2017). Disparities in nominal wages and productivity also incorporate factors such as the cost of living and amenities (Roback, 1982), as well as the distribution of the skilled workforce (Combes, Duranton, & Gobillon, 2008; Young, 2013). In developing economies, part of the productivity gap between rural and urban areas is explained by the informal sector and selection processes (Gollin, Lagakos, & Waugh, 2014). β-convergence regressions are prone to "regression-to-the-mean" bias (Friedman, 1992; Quah, 1993), while "fixed-effects" estimates often used with short panel data tend to be biased toward convergence (Nickell, 1981).

***Research gap***. The authors have not encountered any research in Uzbekistan that examines the regional distribution of labour resources and human capital in relation to production output. In general, when applying the relative distortion index, the extent to which factors such as production prices, informal employment, and labour migration influence the measured level of distortion is rarely analyzed.

***Data and methodology.*** Data and unit of analysis. All data were obtained from the Statistical Information System (SIAT) of the Statistics Agency under the President of the Republic of Uzbekistan and were downloaded in October 2026. The units of analysis are the first-level administrative divisions: the Republic of Karakalpakstan, 12 regions (viloyats), and the city of Tashkent (n = 14). The study period covers the years 2017-2024 (T = 8); this represents the longest period for which data are available at the regional level across all indicators. The year 2025 was excluded from the analysis because the Gross Regional Product (GRP) figures for that year are preliminary, and data regarding higher education

have not yet been published. The list of indicators is presented in Table 1.

**Table 1. Indicators used (SIAT, 14 regions, 2017-2024) [13]**

| Symbol | Indicator and definition | Unit | Role in the analysis |
|---|---|---|---|
| $Y$ | Gross regional product (GRP), current prices | bn soum | Output share $s_i$ (Eqs. 1-4) |
| $Yr$ | GRP in constant 2017 prices, chained from official regional volume growth rates | bn soum, 2017 prices | Constant-price robustness check |
| $E$ | Employed population: formal and informal employment and labour migrants working abroad | thousand persons | Total labour; $\hat{\gamma}_E$ |
| $F$ | Average number of employees in legal entities (formal employment) | persons | Formal labour; $\hat{\gamma}_F$ |
| $H$ | Employees with higher education in legal entities | persons | Human capital; $\hat{\gamma}_H$ |
| $w$ | Average nominal monthly wage | soum | Wage bill $W = 12 \cdot w \cdot F$; $\hat{\gamma}_W$ |
| - | Share of the informal economy in GRP | % | Interpretation of results |

Two definitions are particularly important here. According to the methodology of the Statistics Agency, the "employed population" includes migrants working abroad; meanwhile, the categories of "employees" and "employees with higher education" encompass only hired workers employed by legal entities and registered via an official employment record book. Since a portion of the Gross Domestic Product (GDP) is not allocated by region, the shares of production volume are calculated relative to the sum of the Gross Regional Products (GRP).

Relative distribution index. In accordance with Chen and Hu (2011) and Lu et al. (2024), the relative distortion coefficient for factor L in region i and year t is as follows:

$$\hat{\gamma}_{L,it} = \frac{\frac{L_{it}}{L_t}}{s_{it}\frac{\beta_{L,i}}{\beta_L}}, \qquad s_{it} = \frac{Y_{it}}{Y_t},$$

$$\beta_L = \sum_i s_{it}\,\beta_{L,i}, \qquad (1)$$

Here $s_{it}$ represents the region's share of output, and $\beta_{L,i}$ is the output elasticity of the factor. A value of $\hat{\gamma} > 1$ indicates that the region's share of the factor exceeds its output share (i.e., the factor is over-allocated to the region), while $\hat{\gamma} < 1$ indicates under-allocation. Lu et al. (2024) estimate region-specific elasticities using a production function that incorporates capital stocks; however, since data on regional capital stocks are unavailable for the 14 units over the eight-year period, two alternative approaches are employed here.

Productivity-gap index (common elasticity). If $\beta_{L,i} = \beta_L$ for all regions, Eq. (1) reduces to

$$\hat{\gamma}_{L,it} = \frac{L_{it}/L_t}{Y_{it}/Y_t} = \frac{Y_t/L_t}{Y_{it}/L_{it}}, \qquad (2)$$

which is the reciprocal of relative average labour productivity. This indicator is calculated for total employment ($\hat{\gamma}_E$), formal sector employment ($\hat{\gamma}_F$) and employees with higher education ($\hat{\gamma}_H$).

Wage-gap index (region-specific elasticity). Under conditions of competition in the markets for factors of production, the output elasticity of labour is equal to labour's share in income: $\beta_{F,i} = W_i/Y_i$, where $W_i$ is the formal wage bill (average monthly wage × 12 × formal employees). Substituting into Eq. (1) gives

$$\hat{\gamma}_{W,it} = \frac{F_{it}/F_t}{W_{it}/W_t} = \frac{\bar{w}_t}{w_{it}}, \qquad (3)$$

the ratio of the national average wage to the regional wage. This approach allows for regional variations in elasticity indicators; however, it covers only formal employment and is influenced by regional living costs and skill levels.

Output volume is measured in current prices (as published) and in constant 2017 prices. The figures for constant prices were calculated by chaining official regional growth rates. This is because changes in relative prices specifically, fluctuations in metal prices, as seen in the Navoi region can alter the shares of output, even if the actual volume of production remains unchanged.

Aggregate measures and counterfactual. Dispersion is measured by the standard deviation (SD) of ln $\hat{\gamma}$ across regions. To gauge the cost of misallocation, let regional output be $Y_i = A_i L_i^{\beta}$, where $A_i$ absorbs capital, land and technology, which are held fixed in place. Output is maximised when marginal products are equal, i.e., $L_i^* = L \cdot A_i^{1/(1-\beta)} / \Sigma_j A_j^{1/(1-\beta)}$, and the potential gain is

$$Gain = \frac{\sum_i A_i\,(L_i^*)^{\beta}}{\sum_i Y_i} - 1, \qquad (4)$$

Because β is not identified, results are reported for β = 0,3-0,6. The gain is an upper bound that ignores migration costs, congestion, skill differences and the mobility of capital.

Dagum Gini decomposition. Regional differences in $\hat{\gamma}$ are decomposed with the Dagum (1997) Gini coefficient into within-zone ($G_w$), net between-zone ($G_{nb}$) and transvariation ($G_t$) components, $G = G_w + G_{nb} + G_t$. Regions are grouped into six economic zones commonly used in Uzbek economic geography: Tashkent (Tashkent City, Tashkent region), Fergana Valley (Andijan, Namangan, Fergana), Mirzachul (Syrdarya, Jizzakh), Zarafshan (Samarkand, Bukhara, Navoi), Southern (Kashkadarya, Surkhandarya) and Lower Amudarya (Karakalpakstan, Khorezm). Because zones contain two or three regions, a large between-zone share can arise mechanically, so the observed share is compared with 4 999 random assignments of regions to zones of equal size (permutation test).

Convergence tests. σ-convergence is tested by a linear trend in the SD of ln $\hat{\gamma}$; β-convergence is tested by

$$\Delta \ln \hat{\gamma}_{it} = \alpha + b \ln \hat{\gamma}_{i,t-1} + \mu_i + \eta_t + \varepsilon_{it}, \qquad (5)$$

where b < 0 indicates convergence. Three variants are estimated: pooled OLS (absolute convergence), two-way fixed effects, and a long-difference cross-section of the 2017-2024 change on the 2017 level. With 14 clusters, pooled p-values are taken from a wild cluster bootstrap with Webb weights and 1 999 replications (Cameron, Gelbach, & Miller, 2008; Webb, 2023). The fixed-effects estimate carries a Nickell (1981) bias of about -(1+b)/(T-1), large for T = 7, and is not used as evidence of convergence.

Robustness. Results are re-estimated without Navoi and Tashkent City, with Tashkent City and Tashkent region merged (their boundary changed: Tashkent City's population grew by 4,8% in 2021 and 6,2% in 2022 against 1,7-3,3% in other years), and for 2019-2024.

**Research results.**

Regional pattern of allocation. Table 2 and Figure 1 show the indices. Measured against current-price output, total employment was over-allocated in 11 of the 14 regions in 2024 and strongly under-allocated in Navoi ($\hat{\gamma}_E$ = 0,31) and Tashkent City (0,44), with Tashkent region also below 1 (0,77). The highest values were in Surkhandarya (1,69), Fergana (1,56), Karakalpakstan (1,53), Namangan (1,51) and Kashkadarya (1,44). These are the regions where output per employed person is lowest.

**Table 2. Relative allocation indices by region, 2017 and 2024 [13]**

| Region | Zone | $\hat{\gamma}_E$ 2017 | $\hat{\gamma}_E$ 2024 | $\hat{\gamma}_E$ 2024, const. prices | $\hat{\gamma}_F$ 2024 | $\hat{\gamma}_H$ 2017 | $\hat{\gamma}_H$ 2024 | $\hat{\gamma}_W$ 2024 |
|---|---|---|---|---|---|---|---|---|
| Surkhandarya | Southern | 1,34 | 1,69 | 1,42 | 1,22 | 1,02 | 1,35 | 1,34 |
| Fergana | Fergana V. | 1,42 | 1,56 | 1,41 | 1,35 | 1,03 | 1,12 | 1,36 |
| Karakalpakstan | L. Amudarya | 1,10 | 1,53 | 1,42 | 1,47 | 1,36 | 1,53 | 1,19 |
| Namangan | Fergana V. | 1,30 | 1,51 | 1,31 | 1,15 | 0,97 | 1,00 | 1,38 |
| Kashkadarya | Southern | 1,10 | 1,44 | 1,28 | 1,09 | 1,05 | 1,15 | 1,35 |
| Samarkand | Zarafshan | 1,15 | 1,37 | 1,19 | 1,03 | 0,99 | 1,16 | 1,32 |
| Khorezm | L. Amudarya | 1,26 | 1,36 | 1,37 | 1,22 | 1,15 | 1,12 | 1,24 |
| Andijan | Fergana V. | 1,35 | 1,34 | 1,31 | 1,01 | 0,94 | 0,92 | 1,16 |
| Jizzakh | Mirzachul | 1,01 | 1,20 | 1,19 | 1,04 | 1,11 | 1,15 | 1,31 |
| Syrdarya | Mirzachul | 1,02 | 1,15 | 1,04 | 1,15 | 0,92 | 1,09 | 1,24 |
| Bukhara | Zarafshan | 0,97 | 1,01 | 0,96 | 1,04 | 0,96 | 1,07 | 1,23 |

| Region | Zone | $\hat{\gamma}_E$ 2017 | $\hat{\gamma}_E$ 2024 | $\hat{\gamma}_E$ 2024, const. prices | $\hat{\gamma}_F$ 2024 | $\hat{\gamma}_H$ 2017 | $\hat{\gamma}_H$ 2024 | $\hat{\gamma}_W$ 2024 |
|---|---|---|---|---|---|---|---|---|
| Tashkent region | Tashkent | 0,90 | 0,77 | 0,82 | 0,86 | 0,68 | 0,65 | 1,09 |
| Tashkent City | Tashkent | 0,48 | 0,44 | 0,45 | 0,93 | 1,16 | 1,09 | 0,61 |
| Navoi | Zarafshan | 0,54 | 0,31 | 0,53 | 0,49 | 0,74 | 0,45 | 0,77 |

*Note: $\hat{\gamma} > 1$ - the region's share of the factor exceeds its output-weighted share (over-allocation); $\hat{\gamma} < 1$ - under-allocation; E - total employment; F - formal employees; H - employees with higher education; W - wage-gap index (Eq. 3). Regions are ordered by $\hat{\gamma}_E$ in 2024.*

Three features qualify this reading. First, formal-employment indices are much closer to 1: in Andijan, Samarkand and Kashkadarya $\hat{\gamma}_F$ is 1,01-1,09 while $\hat{\gamma}_E$ is 1,34-1,44. Because total employment includes informal workers and migrants abroad, whose output is not in regional GRP, much of the "excess" labour lies outside the formal sector. Second, Navoi's position is largely a price effect: its share of current-price GRP rose from 5,8% in 2017 to 9,8% in 2024, while its share of constant-price GRP stayed at 5,7-5,9%. In constant prices its $\hat{\gamma}_E$ was 0,53 in both years. Third, the higher-education index orders regions differently: Tashkent City holds slightly *more* highly educated employees than its output share ($\hat{\gamma}_H$ = 1,09), Tashkent region (0,65) and Navoi (0,45) fewer, and Karakalpakstan the most (1,53). The wage-gap index compresses the range to 0,61 (Tashkent City) - 1,38 (Namangan): formal wages were 1,65 times the national average in Tashkent City and 1,29 in Navoi, but 0,72-0,74 in Namangan, Surkhandarya, Fergana and Kashkadarya.

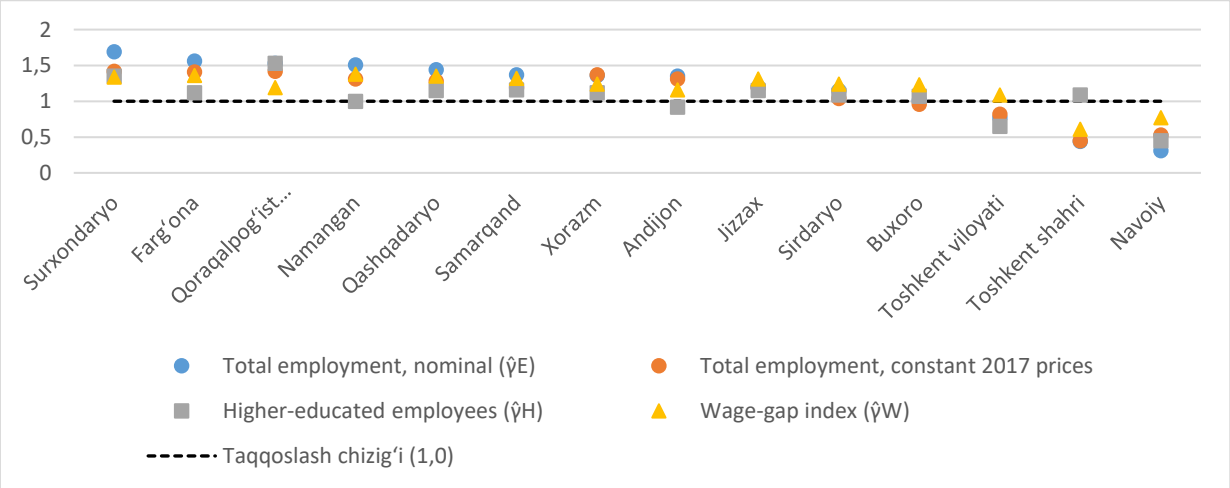


**Figure 1. Relative allocation indices by region, 2024 [13]**

***Kashkadarya***. Kashkadarya illustrates a region whose labour share has grown faster than its output. Its $\hat{\gamma}_E$ rose from 1,10 in 2017 to 1,44 in 2024 in current prices and from 1,10 to 1,28 in constant prices; only Karakalpakstan (+29%) and Jizzakh (+18%) recorded larger constant-price increases than Kashkadarya (+16%). Part of the rise in 2024 reflects a jump in recorded employment (from 1 220,1 to 1 296,3 thousand, +6,2% in one year), larger than in any earlier year of the period. The formal-employment index (1,09) and the higher-education index in constant prices (1,02) are close to 1, while the wage-gap index rose from 1,10 to 1,35, i.e., formal wages in the region fell from 0,91 to 0,74 of the national average. The region's misallocation is therefore concentrated in informal and migrant employment and in relative wages, not in the number of highly educated employees.

**Dispersion and σ-convergence.** Figure 2 and Table 3 show the evolution of dispersion. In current prices the SD of ln $\hat{\gamma}_E$ rose from 0,317 in 2017 to 0,485 in 2024, with a significant positive trend (slope 0,019 per year, p = 0,005); the same holds for formal and higher-educated employees. This would suggest growing misallocation - σ-divergence. In constant prices, however, the picture changes: dispersion of total employment rose only from 0,317 to 0,354 (slope 0,004, p = 0,014), and for formal (p = 0,63) and higher-

educated employees (p = 0,23) there is no significant trend. Most of the measured divergence is thus a relative-price effect rather than a change in the allocation of workers. The wage-gap index, which does not depend on output prices, shows a modest but significant increase in dispersion (0,170 to 0,228; p = 0,001), driven by rising relative wages in Tashkent City.

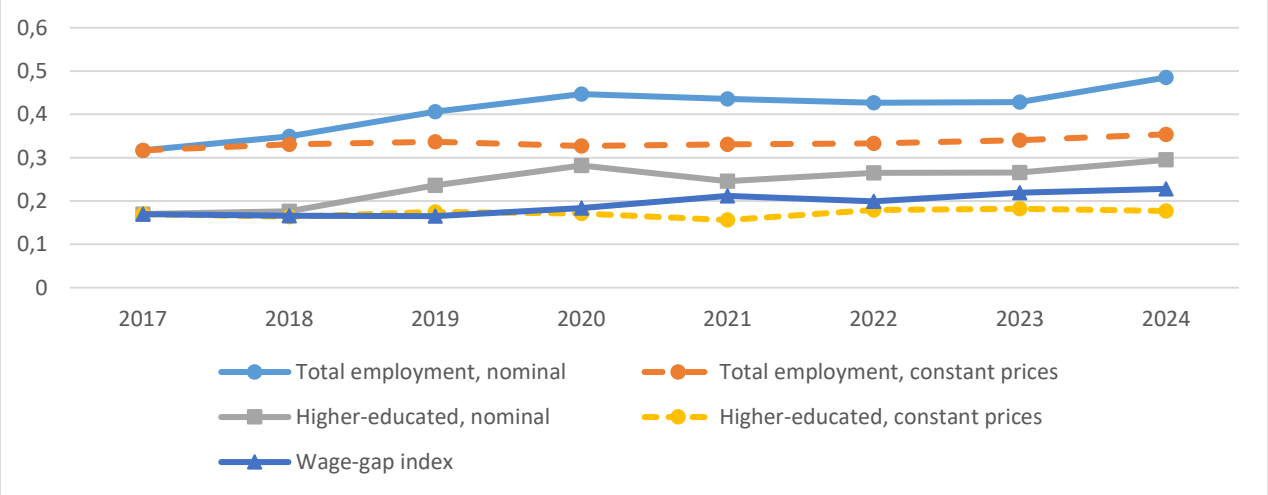


**Figure 2. Dispersion of relative allocation indices, 2017-2024 [13]**

**Table 3. σ-convergence: SD of ln $\hat{\gamma}$ across regions and robustness [13]**

| Specification | 2017 | 2019 | 2024 | Trend per year | p-value |
|---|---|---|---|---|---|
| Total employment, current prices | 0,317 | 0,406 | 0,485 | 0,019 | 0,005 |
| Total employment, constant prices | 0,317 | 0,337 | 0,354 | 0,004 | 0,014 |
| Formal employees, constant prices | 0,123 | 0,105 | 0,131 | 0,001 | 0,632 |
| Higher-educated, current prices | 0,169 | 0,236 | 0,295 | 0,016 | 0,006 |
| Higher-educated, constant prices | 0,169 | 0,175 | 0,177 | 0,002 | 0,232 |
| Wage-gap index | 0,170 | 0,165 | 0,228 | 0,010 | 0,001 |
| Total employment, excl. Navoi and Tashkent City | 0,143 | 0,192 | 0,209 | 0,009 | 0,014 |
| Total employment, Tashkent merged (n = 13) | 0,281 | 0,382 | 0,464 | 0,022 | 0,006 |

*Note: trend - OLS slope of the SD on year, 2017-2024 (8 observations); p-values are indicative given the short series. Excluding the two outliers and merging Tashkent are computed in current prices.*

Excluding Navoi and Tashkent City more than halves dispersion but leaves a positive current-price trend; merging Tashkent leaves results unchanged; for 2019-2024 alone no current-price trend is significant at 5%, because most of the increase occurred in 2018-2020.

Potential output gains. Table 4 reports the counterfactual gains from Eq. (4). Reallocating total employment towards output would raise aggregate output by 3,1-12,3% in 2017 and by 4,1-16,2% in 2024 in constant prices, depending on β. Reallocating formal employees would raise it by less than 1,2% in every year. In current prices the gains are larger (up to 28% for total employment in 2024) because Navoi's price-driven output share inflates the apparent productivity gap. Excluding Navoi and Tashkent City, the current-price gain for total employment in 2024 falls to 1,3-5,0%.

**Table 4. Potential output gain from equalizing marginal products of labour, % [13]**

| Labour measure and price basis | β | 2017 | 2020 | 2024 |
|---|---|---|---|---|
| Total employment, constant prices | 0,3 | 3,1 | 3,1 | 4,1 |
| | 0,5 | 7,7 | 7,8 | 10,3 |
| | 0,6 | 12,3 | 12,3 | 16,2 |
| Formal employees, constant prices | 0,3 | 0,3 | 0,2 | 0,3 |
| | 0,5 | 0,8 | 0,6 | 0,7 |
| | 0,6 | 1,2 | 0,8 | 1,0 |
| Total employment, current prices | 0,5 | 7,7 | 14,0 | 17,8 |
| Formal employees, current prices | 0,5 | 0,8 | 3,3 | 3,6 |

*Note: static, partial-equilibrium upper bound under $Y_i = A_i L_i^{\beta}$ with capital and land fixed in place (Eq. 4).*

**Table 5. Dagum Gini decomposition of relative allocation indices by economic zone [17]**

| Index, year | G | $G_w$, % | $G_{nb}$, % | $G_t$, % | Permutation p |
|---|---|---|---|---|---|
| $\hat{\gamma}_E$ 2017 | 0,140 | 7,9 | 85,7 | 6,4 | - |
| $\hat{\gamma}_E$ 2024 | 0,182 | 7,9 | 85,0 | 7,1 | 0,087 |
| γE 2024, const. prices | 0,148 | 6,9 | 88,8 | 4,4 | - |
| $\hat{\gamma}_H$ 2017 | 0,088 | 9,2 | 65,0 | 25,9 | - |
| $\hat{\gamma}_H$ 2024 | 0,123 | 11,5 | 70,8 | 17,7 | 0,602 |
| $\hat{\gamma}_H$ 2024, const. prices | 0,093 | 9,8 | 67,1 | 23,1 | - |

*Note: G - overall Dagum Gini; $G_w$, $G_{nb}$, $G_t$ - within-zone, net between-zone and transvariation contributions in % of G. Permutation p - share of 4 999 random assignments of regions to zones of equal size with a between-zone share ($G_{nb}$ + $G_t$) at least as large as observed. Source: authors' calculations.*

This seems to replicate Lu et al.'s (2024) finding that between-group differences dominate. However, with six zones of two or three regions, random grouping yields a between-zone share of about 89% on average; the observed share is only marginally higher for total employment (p = 0,087) and not higher for higher-educated employees (p = 0,60). Regional differences are driven by individual units - Tashkent City and Navoi versus Surkhandarya, Fergana and Karakalpakstan - not by zones. Within-zone inequality is highest in Zarafshan (Navoi versus Samarkand and Bukhara; within-zone Gini 0,26 in 2024).

β-convergence. Table 6 reports Eq. (5). In pooled OLS the coefficient on the lagged level is positive for total employment (b = 0,049; wild bootstrap p = 0,049, i.e., marginal divergence) and not significantly different from zero for the other indices according to the wild cluster bootstrap; the long-difference cross-section gives the same picture. There is thus no evidence of absolute β-convergence; if anything, regions with higher over-allocation in current prices drifted further from 1. In constant prices all pooled and long-difference coefficients are close to zero and insignificant. The two-way fixed-effects estimates for $\hat{\gamma}_E$ and $\hat{\gamma}_H$ are large and negative (b ≈ -0,41 to -0,56), but the Nickell bias alone is about -0,17 for b near zero, and the pooled and cross-section estimates show no convergence; they are therefore read as mean reversion around region-specific levels and noise, not as evidence that misallocation is disappearing.

**Table 6. β-convergence of ln $\hat{\gamma}$, 2017-2024 [13]**

| Index | Pooled b (SE) | WCB p | Two-way FE b (SE) | Long-difference b (SE) | p |
|---|---|---|---|---|---|
| **$\hat{\gamma}_E$, current prices** | 0,049 (0,012) | 0,049 | -0,433 (0,058) | 0,064 (0,045) | 0,157 |
| **$\hat{\gamma}_H$, current prices** | 0,046 (0,023) | 0,253 | -0,412 (0,045) | 0,068 (0,065) | 0,296 |
| **$\hat{\gamma}_W$** | 0,036 (0,024) | 0,509 | -0,227 (0,168) | 0,036 (0,043) | 0,405 |
| **$\hat{\gamma}_E$, constant prices** | 0,012 (0,005) | 0,135 | -0,550 (0,101) | 0,011 (0,007) | 0,086 |
| **$\hat{\gamma}_H$, constant prices** | -0,015 (0,013) | 0,271 | -0,563 (0,185) | -0,000 (0,007) | 0,946 |

*Note: dependent variable $\Delta \ln \gamma_{it}$ (pooled and FE, 98 observations) or the average annual change 2017-2024 (long difference, n = 14). Pooled and FE standard errors are clustered by region; WCB p - wild cluster bootstrap p-value (Webb weights, 1 999 replications); long-difference standard errors are HC3.*

**Allocation and efficiency.** In the authors' companion DEA analysis of the same regions, Kashkadarya, Navoi and Surkhandarya lie on the efficiency frontier and Tashkent City has the lowest score. The rank correlation between DEA efficiency (CCR) and the allocation indices is weak and insignificant: Spearman ρ = 0,21 (p = 0,46) for ln $\hat{\gamma}_E$, -0,03 (p = 0,91) for ln $\hat{\gamma}_H$ and 0,43 (p = 0,13) for |ln $\hat{\gamma}_H$|. Efficiency and allocation are thus distinct dimensions: Kashkadarya is DEA-efficient yet holds much more labour than its output share, while Navoi is efficient and under-allocated. With 14 units only large associations could have been detected.

**Discussion.** First, labour in Uzbekistan is far from proportional to output across regions, but most of the gap lies between the formal and the informal-plus-migrant segment of the labour force. Regions with higher $\hat{\gamma}_E$ tend to have larger informal economies: the rank correlation between $\hat{\gamma}_E$ and the informal share of GRP in 2024 is ρ = 0,56 (p = 0,04), against ρ = 0,45 (p = 0,11) for $\hat{\gamma}_F$; the informal share was 41-47% in Surkhandarya, Kashkadarya and Khorezm and 15-16% in Navoi and Tashkent City. Because employment includes migrants abroad, part of the measured over-allocation is not domestic misallocation at all: those workers produce elsewhere and contribute remittances, not GRP. SIAT does not publish regional migration series that would separate the two.

Second, the price basis is not a technicality. With current-price GRP, as is usual in applications of the relative distortion index, one would conclude that misallocation rose sharply after 2018; in constant prices most of that rise disappears. For resource-rich regions the productivity-gap index measures resource rents as much as labour distortions (Restuccia & Rogerson, 2017), so studies of commodity-exporting economies should report both price bases.

Third, unlike Lu et al. (2024) for China, there is no σ- or β-convergence, and the dominance of between-group differences is not robust to the small number of units per group. This does not contradict their findings, given different settings, but shows that these tools need small-sample diagnostics when applied to few regions. For human capital, $\hat{\gamma}_H$ partly reflects the geography of public services - teachers, doctors and civil servants located by population rather than output - and is better read as the departure of graduates' distribution from market production than as evidence that graduates should move.

The limitations are clear. Without regional capital stock, the common-elasticity index conflates labour distortions with capital intensity; without regional price levels, the wage-gap index overstates real wage differences; employment includes migrants; and trend tests rest on eight annual observations. All results are descriptive and do not identify the causes of misallocation - migration costs, housing, registration rules, credit or public employment policies.

**Conclusion**

Using only official SIAT statistics, this paper measured the allocation of labour and human capital across Uzbekistan's 14 regions relative to output in 2017-2024. Labour is over-allocated in the southern, Fergana Valley and Lower Amudarya regions and under-allocated in Tashkent City and Navoi, but most of the gap concerns informal and migrant employment; formal and highly educated employees are allocated much closer to output. The apparent divergence in current prices is largely a relative-price effect, there is no robust convergence or divergence in constant prices, and differences between economic zones are no larger than random grouping would produce. The main potential gain therefore lies less in moving formal or highly educated workers than in raising the productivity of informal employment and creating formal jobs in labour-abundant regions such

as Kashkadarya. Regional capital stock, regional labour migration and regional price indices are the three statistical additions that would make such measurement more reliable.

**References:**


1. Aoki, S. (2012). A simple accounting framework for the effect of resource misallocation on aggregate productivity. *Journal of the Japanese and International Economies*, 26(4), 473–494. https://doi.org/10.1016/j.jjie.2012.08.001
2. Brandt, L., Tombe, T., & Zhu, X. (2013). Factor market distortions across time, space and sectors in China. *Review of Economic Dynamics*, 16(1), 39–58. https://doi.org/10.1016/j.red.2012.10.002
3. Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2008). Bootstrap-based improvements for inference with clustered errors. *Review of Economics and Statistics*, 90(3), 414–427. https://doi.org/10.1162/rest.90.3.414
4. Chen, Y., & Hu, W. (2011). Distortions, misallocation and losses: Theory and application. *China Economic Quarterly*, 10(4), 1401–1422. (In Chinese)
5. Combes, P.-P., Duranton, G., & Gobillon, L. (2008). Spatial wage disparities: Sorting matters! *Journal of Urban Economics*, 63(2), 723–742. https://doi.org/10.1016/j.jue.2007.04.004
6. Dagum, C. (1997). A new approach to the decomposition of the Gini income inequality ratio. *Empirical Economics*, 22(4), 515–531. https://doi.org/10.1007/BF01205777
7. Friedman, M. (1992). Do old fallacies ever die? *Journal of Economic Literature*, 30(4), 2129–2132.
8. Gollin, D., Lagakos, D., & Waugh, M. E. (2014). The agricultural productivity gap. *Quarterly Journal of Economics*, 129(2), 939–993. https://doi.org/10.1093/qje/qjt056
9. Hsieh, C.-T., & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics*, 124(4), 1403–1448. https://doi.org/10.1162/qjec.2009.124.4.1403
10. Hsieh, C.-T., & Moretti, E. (2019). Housing constraints and spatial misallocation. *American Economic Journal: Macroeconomics*, 11(2), 1–39. https://doi.org/10.1257/mac.20170388
11. 12. Lu, W., Peng, L., & Fang, N. (2024). The impact of human capital misallocation on green economy efficiency: Empirical analysis of Chinese urban agglomerations. *Heliyon*, 10, e32695. https://doi.org/10.1016/j.heliyon.2024.e32695
12. (2026). *National Statistics Committee of the Republic of Uzbekistan. SIAT – Statistical information and analytical system [Database]*. https://siat.stat.uz (accessed October 2026).
13. Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, 49(6), 1417–1426. https://doi.org/10.2307/1911408
14. Quah, D. (1993). Galton's fallacy and tests of the convergence hypothesis. *Scandinavian Journal of Economics*, 95(4), 427–443. https://doi.org/10.2307/3440905
15. Restuccia, D., & Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics*, 11(4), 707–720. https://doi.org/10.1016/j.red.2008.05.002
16. Restuccia, D., & Rogerson, R. (2017). The causes and costs of misallocation. *Journal of Economic Perspectives*, 31(3), 151–174. https://doi.org/10.1257/jep.31.3.151
17. Roback, J. (1982). Wages, rents, and the quality of life. *Journal of Political Economy*, 90(6), 1257–1278. https://doi.org/10.1086/261120
18. Siddikov, A. J. (2022). Development of a critical level of indicative indicators for diagnosing the macroeconomic balance of Uzbekistan. *ISJ Theoretical & Applied Science*, 02 (106), 307-315. Soi: http://s-o-i.org/1.1/TAS-02-106-37 Doi: https://dx.doi.org/10.15863/TAS.2022.02.106.37
19. Vollrath, D. (2014). The efficiency of human capital allocations in developing countries. *Journal of Development Economics*, 108, 106–118. https://doi.org/10.1016/j.jdeveco.2014.01.008
20. Webb, M. D. (2023). Reworking wild bootstrap-based inference for clustered errors. *Canadian Journal of Economics*, 56(3), 839–858. https://doi.org/10.1111/caje.12661
21. Young, A. (2013). Inequality, the urban-rural gap, and migration. *Quarterly Journal of Economics*, 128(4),1727–1785. https://doi.org/10.1093/qje/qjt025