How Inflation Erodes Real Household Incomes in Uzbekistan: Regional Panel Evidence and Forecasts for 2026–2028

Rakhimov Nuritdin Rakhmanovich

PhD in Economics, Tashkent State University of Economics, Tashkent, Uzbekistan

E-mail: raximovnr61@mail.ru

Abstract

Using official data for Uzbekistan's 14 regions over 2010–2025, this study examines how inflation and unemployment shape the growth of real per capita household income and how well that growth can be forecast. It combines cross-sectional dependence tests, a dynamic panel ARDL model with Driscoll–Kraay standard errors, Mean Group and two-way fixed-effects estimators and a pseudo-real-time forecast comparison. Inflation acts with a one-year lag: a one-point rise in last year's inflation lowers real income growth by 0.78–1.11 points, and in 2019–2025 a one-off inflation shock reduced the real income level by about 1%. The negative unemployment effect found in a national OLS regression (−2.45) disappears once the 2018 change in unemployment measurement and common shocks are controlled for. A parsimonious dynamic panel model with a regime shift cuts the forecast RMSE by 27% relative to a naive forecast (Diebold–Mariano $p = 0.012$). Real income growth is projected at 6.4–6.5% a year in 2026–2028, but an inflation overshoot of 3 points in 2027 would lower growth in 2028 by 3.6 points. Disinflation and forward-looking indexation are therefore central to protecting real incomes.

Keywords

real household income; inflation; unemployment; regional panel; Driscoll–Kraay standard errors; forecast evaluation; inflation targeting; Uzbekistan.

JEL classification: C23, C53, E24, E31, O53.

1. Introduction

Real household income is the most direct gauge of whether macroeconomic policy improves living standards. Inflation erodes the purchasing power of nominal incomes until wages and transfers catch up, and because expectations eventually become built into nominal incomes, its lasting cost depends on how quickly that catching-up occurs [1]. The burden falls most heavily on households whose incomes are fixed in nominal terms [2]. Uzbekistan is an instructive case. After the foreign exchange liberalisation of September 2017, December-on-December inflation reached 14.3–15.2% in 2017–2019, and in November 2019 the central bank began a gradual move to inflation targeting. Meanwhile, the average growth of real per capita income slowed from 13.5% in 2010–2017 to 5.5% in 2018–2025 [3].

The usual first approach, a national OLS regression of real income growth on inflation and unemployment, ignores three features of the data. First, unemployment measurement changed in 2018: the rate jumped from 5.8% to 9.3% in a single year, and the Ministry of Employment and Labour Relations attributed the jump to better measurement rather than to rising joblessness [4]. Second, regions move together under common macroeconomic shocks, so conventional standard errors are far too small. Third, the forecasting performance of such regressions is rarely checked out of sample.

This thesis estimates the effect of inflation and unemployment on real per capita income growth in Uzbekistan's regions with tools that are robust to cross-sectional dependence, namely Driscoll–Kraay standard errors [5], the CD test [6] and Mean Group estimates [7], and compares forecasting models in pseudo-real time with Diebold–Mariano tests [8]. Three hypotheses are tested: *H1*, inflation reduces real income growth with a lag; *H2*, higher unemployment slows real income growth; and *H3*, a parsimonious dynamic model that allows for the regime shift forecasts better than models augmented with macroeconomic regressors.

2. Literature review

In the Phillips-curve tradition, inflation and unemployment move in opposite directions, but Friedman [1] argued that the trade-off is temporary: once inflation expectations are built into wages and other nominal incomes, unemployment returns to its natural rate, and only the losses of those whose incomes adjust slowly remain. Easterly and Fischer [2] show that high inflation is associated with a smaller income share of the bottom quintile and a lower real minimum wage. Regional panels, for their part, are dominated by common shocks: the CD test [6] detects the resulting cross-sectional dependence, Driscoll–Kraay standard errors [5] remain consistent in its presence, and the Mean Group estimator [7] lets the slopes differ across regions. Because a good in-sample fit does not guarantee forecasting accuracy, competing models are best compared out of sample with the Diebold–Mariano test [8].

Recent work on Uzbekistan points to a structural change in macroeconomic relationships after the 2017 liberalisation. Farmonov et al. [9] find that the short-run elasticity of international reserves to the gold price rose from 0.49 to 0.90 after 2017 and that a dynamic model outperforms an autoregressive benchmark out of sample. In an earlier paper [10], we estimated dynamic panel models of real household income growth for the regions of Uzbekistan; this thesis condenses that analysis and focuses on what it implies for protecting incomes during disinflation. Mardonova and Farmonov [11] relate education expenditure and tertiary enrolment to growth in an augmented Solow framework estimated by ARDL methods, and Jidelbekova and Farmonov [12] study urbanisation, growth and electricity consumption with ARDL and Toda–Yamamoto techniques. Apart from [10], no study has estimated the effect of inflation and unemployment on regional real incomes in Uzbekistan while accounting for statistical breaks and cross-sectional dependence.

3. Data and methods

The data come from the SIAT database of the National Statistics Committee [3]

and cover 14 regions over 2010–2025 (224 observations; 210 once the lag is taken). The dependent variable y_{it} is the growth of real per capita total income in region i and year t (%); the unemployment rate u_{it} is computed from the economically active and employed population; and inflation π_t is the national December-on-December change in the CPI, which acts as a common factor for all regions. The dummy S2018 (one from 2018 onwards) captures the post-liberalisation regime, the new unemployment methodology [4] and the updated CPI introduced in the same year, and D2020 marks the pandemic. Cross-sectional dependence is tested with the CD statistic [6] and stationarity with the CIPS test, using critical values simulated for $N = 14$ and $T = 16$. The main model is a dynamic panel ARDL(1,1,0) specification with regional fixed effects:

$$y_{it} = \alpha_i + \rho\, y_{i,t-1} + \beta_0 \pi_t + \beta_1 \pi_{t-1} + \gamma\, u_{it} + \delta_1 \mathrm{S2018}_t + \delta_2 \mathrm{D2020}_t + \varepsilon_{it} \quad (1)$$

where α_i are regional effects, ρ measures persistence, β_0 and β_1 are the effects of current and lagged inflation, and γ is the effect of unemployment. Since y_{it} is a growth rate, the cumulative multipliers

$$\theta_\pi = \frac{\beta_0 + \beta_1}{1-\rho}, \qquad \theta_u = \frac{\gamma}{1-\rho} \qquad (2)$$

give the permanent effect, in per cent, of a one-off one-point shock on the level of real income. Inference relies on Driscoll–Kraay standard errors [5]. As robustness checks, the model is re-estimated for 2019–2025, a period with a homogeneous statistical methodology, with the Mean Group estimator [7] and with two-way fixed effects, in which year effects absorb all common shocks. For forecasting, a parsimonious dynamic panel model with a regime shift (DPM-RS) is proposed:

$$y_{it} = \alpha_i + \rho\, y_{i,t-1} + \delta\, \mathrm{S2018}_t + \kappa\, \mathrm{D2018}_t + \lambda\, \mathrm{D2020}_t + \varepsilon_{it} \qquad (3)$$

where D2018 is a 2018 impulse. Every model is re-estimated at each origin from 2018 to 2024 and used to forecast the following year (98 regional and 7 national forecasts). DPM-RS is compared with a naive forecast, the historical mean, a static fixed-effects model, the ARDL model (1) and an AR (1) model without the regime shift,

using the RMSE, Theil's U and the Diebold–Mariano test [8] with a small-sample correction. Prediction intervals come from 20,000 Monte Carlo simulations with a year-block bootstrap of the residuals, and inflation scenarios are computed as deviations from the baseline:

$$\Delta\hat{y}_t = \rho\,\Delta\hat{y}_{t-1} + \beta_0\,\Delta\pi_t + \beta_1\,\Delta\pi_{t-1} \quad (4)$$

where $\Delta\pi_t$ is the gap between the scenario and the central bank's inflation path, and the coefficients are the 2019–2025 ARDL estimates.

4. Results and discussion

Regional real income grew by 13.6% a year on average in 2010–2017 but by only 5.1% in 2018–2025, while inflation rose from 7.6% to 11.1% and unemployment from 5.2% to 8.1%, with a jump of 3.5 points between 2017 and 2018 alone. The national correlation between income growth and unemployment is −0.57 overall but was positive (+0.21) before 2018, so the negative sign comes mainly from the shift in means between the two regimes. Income growth is only weakly correlated with current inflation (−0.25) but strongly with lagged inflation (−0.66). Common year effects explain 76% of the within-region variation, the CD statistics (29.7 and 37.3) confirm strong cross-sectional dependence, income growth is stationary (CIPS $p < 0.001$), and unemployment is highly persistent ($p = 0.326$ once the 2018 shift is allowed for).

Table 1 reports the estimates. The static national OLS model (column 1) reproduces the familiar result, a strongly negative unemployment effect (−2.454; $p = 0.027$), but once S2018 and D2020 are added (column 2), the coefficient falls to −0.701 and becomes insignificant ($p = 0.610$): the apparent unemployment effect largely reflects the 2018 statistical break. In the main dynamic panel model (column 3), lagged inflation has a coefficient of −0.841 ($p = 0.062$) and unemployment one of −0.058 ($p = 0.944$); dropping one region at a time keeps the lagged-inflation coefficient between −1.01 and −0.72. In 2019–2025 (column 4) the effect is sharper: the lagged coefficient is −1.110

(p = 0.002), and the cumulative multiplier of −1.021 (p = 0.001) implies that a one-off one-point inflation shock lowers the level of real income by about 1%. The Mean Group estimates (column 5) confirm the result (−0.783; p = 0.018), with a negative coefficient in 11 of the 14 regions, whereas unemployment remains insignificant in the Mean Group and two-way fixed-effects models, as does its change (−0.679; p = 0.492). *H1* is therefore supported and *H2* rejected.

In the pseudo-real-time comparison (Table 2), DPM-RS has the smallest errors on all criteria (RMSE of 5.60 points for the regions and 4.31 for the national series; Theil's U of 0.73), and its advantage over the naive forecast is significant (DM = 3.02; p = 0.012). Models that use the realised values of inflation and unemployment do not help (U = 0.88 for the static model and 1.34 for the ARDL model), and ignoring the regime shift produces systematic over-prediction (mean error −3.83 points). The gain over the static and no-break models is not significant in the seven-year window (p = 0.17 and 0.20), so *H3* is only partly supported, but DPM-RS is virtually unbiased (mean error 0.17) and well calibrated: its 80% intervals cover 87 of the 98 regional outcomes (88.8%).

Table 1. Estimates of real income growth models (dependent variable: *y*)

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	OLS	OLS	FE-DK	FE-DK	MG	TWFE-DK
Sample	national	national	14 regions	14 regions	14 regions	14 regions
Period	2010–2025	2010–2025	2011–2025	2019–2025	2011–2025	2011–2025
y_{t-1}	–	–	0.124	−0.256***	0.088	−0.111***
			(0.124)	(0.030)	(0.052)	(0.036)

π_t	0.604	0.500	0.504	−0.172	0.572***	–
	(0.630)	(0.632)	(0.343)	(0.187)	(0.155)	
π_{t-1}	–	–	−0.841*	−1.110***	−0.783**	–
			(0.414)	(0.220)	(0.289)	
u_t	−2.454**	−0.701	−0.058	0.718**	−0.444	−0.408
	(0.984)	(1.336)	(0.814)	(0.222)	(0.537)	(0.791)
S2018	–	−6.901*	−3.328	–	−3.030**	–
		(3.842)	(2.771)		(1.160)	
D2020	–	−6.688	−4.065	−5.754***	−3.443***	–
		(6.782)	(2.677)	(1.274)	(0.919)	
Constant	20.084***	13.340**	–	–	–	–
	(4.964)	(5.842)				
θ_π (cumulative)	–	–	−0.385	−1.021***	−0.232	–
			(0.678)	(0.174)	(0.354)	
θ_u (cumulative)	–	–	−0.067	0.572**	−0.487	−0.368
			(0.935)	(0.180)	(0.568)	(0.705)
R^2 (within for FE)	0.367	0.528	0.408	0.527	–	0.763
Durbin–Watson	1.06	1.06	–	–	–	–
Residual CD test	–	–	20.37	1.77	–	−2.52
			($p < 0.001$)	($p = 0.077$)		($p = 0.012$)
Observations	16	16	210	98	210	210

Note: standard errors in parentheses: conventional OLS in (1)–(2), Driscoll–Kraay (bandwidth 2) in (3), (4) and (6), Mean Group in (5). In (6), year effects absorb all common variables. θ_π and θ_u are the cumulative multipliers of Eq. (2) (delta method). *** p < 0.01, ** p < 0.05, * p < 0.10. Source: authors' calculations.

Table 2. Pseudo-real-time forecast accuracy (forecasts for 2019–2025)

Model	RMSE (regions)	MAE (regions)	RMSE (national)	Theil's U	DM (*p*)
Naive (random walk)	7.67	6.06	5.97	1.00	–
Historical mean	7.44	5.85	6.19	0.97	0.10 (0.461)
Static FE (π, u)[a]	6.77	5.39	5.84	0.88	2.20 (0.035)
ARDL, model (1)[a]	10.28	7.21	9.75	1.34	−0.73 (0.755)
AR(1)-FE without regime shift	6.86	5.49	5.50	0.89	0.46 (0.330)
DPM-RS (proposed)	5.60	4.33	4.31	0.73	3.02 (0.012)
Coverage of DPM-RS intervals (80% / 95%)	regions: 88.8% / 92.9% (87 and 91 of 98 forecasts); national: 6 / 7 of 7				

Note: [a] uses the realised values of π and u in the forecast year (ex post). Theil's U is the ratio of the regional RMSE to that of the naive forecast; DM is the Diebold–Mariano statistic with a small-sample correction, and the one-sided p-value refers to the superiority of the model over the naive forecast.

In the full-sample DPM-RS model ($\rho = 0.097$; S2018 coefficient −5.80, p = 0.027), the equilibrium growth rate of real income is 6.4%. With inflation following the central bank's November 2026 projection (7.0, 5.0 and 5.0% in 2026–2028), the baseline forecast is 6.5% for 2026 (80% interval: 1.7–12.1%) and 6.4% for 2027–2028 (Figure 1); real per capita income grew by 7.3% in the first half of 2026 [3], close to the point forecast. If inflation is instead 8% in 2027 and 7% in 2028, growth slows by 0.5 points in 2027 and by 3.6 points in 2028, to 2.8%, and the cumulative loss in the real income level reaches 4.1%.

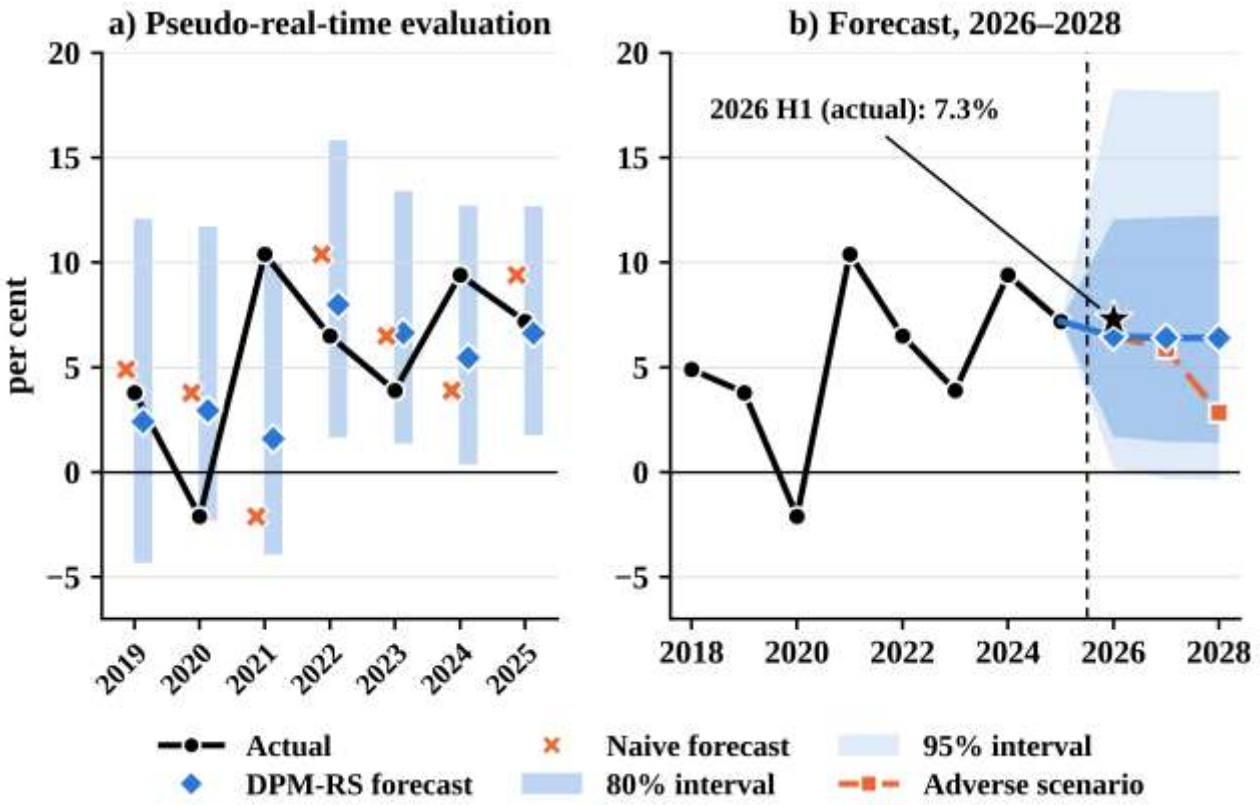


Figure 1. Pseudo-real-time forecasts of DPM-RS (a) and forecasts for 2026–2028 (b)

Note: in (a), each forecast uses only the data available up to the previous year, and the bars show 80% prediction intervals; in (b), intervals come from 20,000 Monte Carlo simulations, the star shows actual real growth in the first half of 2026 [3], and the adverse scenario assumes inflation 3 and 2 points above the central bank's path in 2027–2028.

The central finding is that inflation affects real incomes mainly with a one-year lag. Wages, pensions and social benefits are usually indexed once a year and after the fact, part of December-on-December inflation carries over into the next year's average price level, and inflation erodes savings and fixed nominal incomes such as rents and deposit interest; the lack of catch-up in 2019–2025 fits the evidence that inflation hurts groups with fixed nominal incomes most [2]. The positive but insignificant full-sample coefficient on current inflation (0.504) is not a benefit of inflation: it reflects the 2017 devaluation, which immediately raised the soum value of remittances and foreign-

currency-linked incomes, in line with the post-2017 structural change documented in [9]. Nor does the absence of a robust unemployment effect mean that unemployment is harmless: with high informality and large-scale labour migration, unemployment status says little about household income, which also comes from informal work, self-employment and remittances.

Three policy implications follow. First, bringing inflation down to the 5% target is a key condition for protecting real incomes, since each unexpected point of inflation removes about 1% from their level. Second, indexing pensions, social benefits and the minimum wage to the central bank's inflation forecast, with an in-year correction when actual inflation exceeds it, would shorten the lag. Third, back-casting labour market statistics on a consistent methodology and publishing regional remittance data are needed to measure the income effects of unemployment reliably. The main limitations are the short time dimension (T = 15), the national measurement of inflation and the preliminary data for 2024–2025.

5. Conclusions

Inflation lowers real household income growth with a one-year lag: a one-point rise in last year's inflation slows it by 0.78–1.11 points, and in 2019–2025 a one-off shock cut the real income level by about 1%.

The negative unemployment effect in simple regressions is an artefact of the 2018 methodological change and disappears once the regime shift and common shocks are controlled for.

A parsimonious dynamic panel model with a regime shift cuts forecast errors by 27% relative to a naive forecast and gives calibrated intervals.

Real income is projected to grow by 6.4–6.5% a year in 2026–2028, but an inflation overshoot of 3 points in 2027 would cut growth in 2028 to 2.8%.

References

[1] Friedman, M. (1968). The role of monetary policy. *American Economic Review*, 58(1), 1–17. https://www.jstor.org/stable/1831652

[2] Easterly, W., & Fischer, S. (2001). Inflation and the poor. *Journal of Money, Credit and Banking*, 33(2), 160–178.

[3] National Statistics Committee of the Republic of Uzbekistan. (2026). *SIAT database of socio-economic indicators*: Growth rate of real per capita total income (ID 434), economically active population (ID 554), employed population (ID 567), consumer price index (ID 3003) [Data set]. https://siat.stat.uz/

[4] Tashkent Times. (2019, January). Uzbekistan unemployment rate at 9.3% in 2018. https://www.tashkenttimes.uz/economy/3457-uzbekistan-unemployment-rate-at-9-3-in-2018

[5] Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, 80(4), 549–560. https://doi.org/10.1162/003465398557825

[6] Pesaran, M. H. (2015). Testing weak cross-sectional dependence in large panels. *Econometric Reviews*, 34(6–10), 1089–1117. https://doi.org/10.1080/07474938.2014.956623

[7] Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1), 79–113. https://doi.org/10.1016/0304-4076(94)01644-F

[8] Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics*, 13(3), 253–263. https://doi.org/10.1080/07350015.1995.10524599

[9] Farmonov, B. D., Sabirov, K. K., & Raxmonov, M. R. (2026). Gold and cotton price shocks, exports and international reserves in a gold-dependent economy:

Evidence from Uzbekistan. *International Journal of Statistical Analysis*, 335–351. https://ijstatisticalanalysis.org/index.php/ijsa/article/view/65

[10] Farmonov, B. D., Rakhimov N.R. (2026). The Impact of Inflation and Unemployment on the Real Growth of Household Incomes: Dynamic Panel Evidence and Forecasts for the Regions of Uzbekistan. *Radiance an International jurnal of multidisciplinary research*. 61-81. https://www.radianceonlinejournal.com/index.php/rijms/article/view/35

[11] Mardonova N.A, Farmonov B.D. (2026). Education expenditure, tertiary enrollment and economic growth in uzbekistan: an augmented solow and ardl approach. *Radiance an International jurnal of multidisciplinary research* 38-60. https://www.radianceonlinejournal.com/index.php/rijms/article/view/34

[12] Jidelbekova J, Farmonov B.D. (2026). Urbanization, Economic Growth and Electricity Consumption in Uzbekistan: An ARDL and Toda–Yamamoto Approach. *International Journal of Statistical Analysis*, 143–162. https://ijstatisticalanalysis.org/index.php/ijsa/article/view/88