ACADEMIC JOURNAL
ISSN 2697-2212

Academic Journal of Digital Economy and Stability
Volume 39, Issue 5 | November-2026

Available Online:
https://journal.academicjournal.online/index.php/economics

Article

Forecasting Bank Credit to Small Business with Short Panels: Partial Pooling Versus Country-Specific Trends, With An Application to Uzbekistan

Abror Boshlarovich Inobatov

1. PhD in Economics, Associate Professor, Head of the Department of Economics and Finance Renaissance University, Tashkent, Uzbekistan

* Correspondence: abror21@bk.ru

Abstract: Official statistics on bank lending to micro, small and medium enterprises (MSMEs) are short: for most emerging economies only five to six annual observations exist, and a forecast built on one country's own trend has almost no statistical content. This paper asks whether borrowing strength from other countries improves such forecasts. Using the Asian Development Bank's MSME loan-stock series for 21 economies, we run a rolling-origin forecast evaluation of 105 country–origin–horizon forecasts per method (21 economies × six annual observations, 2019–2024) and compare a random walk, country drift, country log-trend, a pooled cross-country growth rate, and a shrinkage forecast that mixes the country's own drift with the pooled median. At the one-year horizon the shrinkage forecast reduces the mean absolute log error by 29% relative to the random walk (0.083 versus 0.117) and by 18% relative to country drift (0.101); both differences are significant under a country-cluster bootstrap (95% intervals −0.053 to −0.016 and −0.034 to −0.004). Against the random walk the advantage also holds at two years; it is stable when Kazakhstan's definitional break or Uzbekistan itself is removed, and is present in each of the three forecast origins. Empirical 80% intervals built from cross-country errors have leave-one-country-out coverage of 76–79%, although they are not sharper than random-walk intervals. Applied to Uzbekistan, whose MSME loan stock reached 93.4 trillion UZS in 2024 on the ADB definition, the model implies 102.4 trillion in 2025 (80% interval 92.9–117.8) and 134.7 trillion by 2028 (109.2–183.5), close to the 136.9 trillion of the country's own six-point log-trend but well below the upper scenarios (147.6–185.5) built on it, and with a wide interval that the single-country model cannot provide. The results are about nominal local-currency stocks on heterogeneous national definitions and should be read as a forecasting benchmark, not as causal evidence.

Keywords: MSME finance; bank credit; forecast evaluation; partial pooling; short panels; empirical prediction intervals; Uzbekistan

Citation: Inobatov, A. B. Forecasting Bank Credit to Small Business with Short Panels: Partial Pooling Versus Country-Specific Trends, With An Application to Uzbekistan. Academic Journal of Digital Economics and Stability 2026, 39(5), 20-32

Received: 13th Aug 2026
Revised: 28th Sep 2026
Accepted: 15th Oct 2026
Published: 04th Nov 2026

Copyright: © 2026 by the authors. Submitted for open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/)

1. Introduction

Bank credit is the principal external funding source of small firms, which are informationally opaque and rarely access capital markets [1]. Policy targets for MSME lending are therefore routinely expressed as stocks or shares of GDP several years ahead, and their credibility depends on how large future credit can plausibly be. Yet the empirical basis for such projections is thin. National MSME loan statistics are young, definitions change, and, in the Asian Development Bank (ADB) compilation, most economies report no more than six annual observations for 2019–2024 [2].

A common response is to fit a linear or log-linear trend to the national series and extrapolate it, sometimes with "optimistic" and "pessimistic" scenarios. With six observations, one structural break (the 2020 contraction in Uzbekistan, a 12.7% fall in the

stock) dominates the slope, the coefficient of determination is inflated by the common upward drift of nominal series, and in-sample fit says almost nothing about out-of-sample accuracy. A single-country trend model, in short, cannot be validated.

This paper takes the validation problem as its research question. Does a forecast that borrows strength from other countries' growth experience beat country-specific extrapolation, and by how much? The question is the forecasting analogue of the "to pool or not to pool" debate in panel econometrics and of shrinkage toward a grand mean [3]. Our contributions are threefold. First, we provide out-of-sample evidence, from 105 forecasts across 21 economies, on which simple methods work for MSME credit stocks. Second, we show that empirical prediction intervals constructed from cross-country forecast errors are approximately calibrated, which gives policy users a defensible range rather than a point path. Third, we apply the evaluated method to Uzbekistan and compare it with the single-country trend approach, quantifying how far the latter departs [4].

Finance and small-firm growth. Financial development is associated with growth, and cross-country evidence links SME presence with growth, though the causal channel is debated [5]. Credit rationing under asymmetric information and the role of relationship lending imply that MSME credit responds slowly and with common regional shocks, which is why a country's own history is a noisy guide to its future.

Forecast evaluation with short samples. Accuracy should be judged out of sample and with scale-free or log-scale measures. In short panels, parameters estimated country by country have high variance, and restricted or shrunken estimators often forecast better even when the restriction is false. Combining simple forecasts also tends to help. Forecast failures are typically caused by structural breaks and location shifts rather than by parameter noise alone, so robustness to breaks matters. Equal accuracy of nested forecasts is tested with adjustments such as those of Clark & West; we instead use a country-cluster bootstrap, which preserves dependence within countries and requires no distributional assumption [6].

Hypotheses. H1: pooling growth across countries improves one-year accuracy relative to country-specific drift and trend. H2: a shrinkage forecast that mixes country and pooled growth is at least as accurate as pure pooling and more accurate than country-specific methods. H3: relative accuracy gains persist at the two-year horizon. H4: empirical intervals from cross-country errors are approximately calibrated out of sample [7].

Table 1. Forecast methods compared

Method	Forecast of log loans at h years	Interpretation
Random walk	y(T)	No change; ignores growth
Country drift	y(T) + h·g(i)	Country's own mean log growth to date
Country log-trend	OLS of y on t, extended	Standard single-country trend model
Pooled growth	y(T) + h·median g(−i)	Median growth of the other economies
Shrinkage	y(T) + h·[λ·g(i) + (1−λ)·median g(−i)]	Partial pooling; λ = 0.5 fixed ex ante

Source: author. y = log MSME loans; g(i) = mean annual log growth of economy i observed up to origin T; g(−i) = the same for all other economies (leave-one-out).

2. Materials and Methods

2.1 Data

We take "MSME loans outstanding" (year-end stock, local currency) from the country sections (Tables x.3) of the ADB Asia SME Monitor 2025. Of 26 economies with such a table, 21 report all six years 2019–2024; Nepal, Sri Lanka and Viet Nam (missing years)

and Cambodia (no loan row) are excluded. Each economy thus contributes six annual observations, that is, five growth rates, and the panel has 21 × 6 = 126 observations (Appendix, Table A1; file msme_panel.csv). The training windows are short by necessity: at forecast origins 2021, 2022 and 2023 they contain 3, 4 and 5 observations (2, 3 and 4 growth rates). Median annual growth across economies is 8.6% (interquartile range 6.4–12.2%); three economies (Philippines, Singapore, Thailand) and Samoa show declining stocks. Uzbekistan's series (55.4 to 93.4 trillion UZS; Table 8.3) uses the earlier micro-and-small definition, which excludes medium enterprises.

2.2 Forecasting methods

Let L(i,t) denote the MSME loan stock of economy i in year t and y(i,t) = ln L(i,t). The log growth rate, the country's mean growth up to the forecast origin T, and the leave-one-out cross-country benchmark are

$$g(i,t) = y(i,t) - y(i,t-1) \quad (1)$$

$$\bar{g}(i,T) = [y(i,T) - y(i,2019)] / (T - 2019) \quad (2)$$

$$m(-i,T) = \text{median over } j \neq i \text{ of } \bar{g}(j,T) \quad (3)$$

The five forecasts of y(i,T+h) are: random walk, y(i,T); country drift, y(i,T) + h·ḡ(i,T); country log-trend, the OLS fit y = a + b·t on 2019…T extended to T+h; pooled growth, y(i,T) + h·m(−i,T); and the shrinkage forecast

$$\hat{y}(i,T+h) = y(i,T) + h\cdot[\, \lambda\cdot\bar{g}(i,T) + (1-\lambda)\cdot m(-i,T)\,], \quad \lambda = 0.5 \quad (4)$$

which is a convex combination of the country's own growth and the median growth of the other economies [Efron & Morris, 1975; Stock & Watson, 2004]. The level forecast is $\hat{L} = \exp(\hat{y})$. Because m(−i,T) excludes economy i and uses only data up to T, no forecast uses information from the forecast period.

2.3 Evaluation design, loss and inference

For each economy and each forecast origin $T \in \{2021, 2022, 2023\}$ we use only data up to T and forecast h = 1 year (three origins, 63 forecasts per method) and h = 2 years (origins 2021–2022, 42 forecasts per method), as in Figure 1. The forecast error and accuracy measures are

$$e(i,T,h) = \hat{y}(i,T+h) - y(i,T+h) \quad (5)$$

$$MAE = (1/N)\cdot\Sigma\,|e|, \quad RMSE = [\,(1/N)\cdot\Sigma\, e^2\,]^{1/2}, \quad U = RMSE(\text{method}) / RMSE(\text{random walk}) \quad (6)$$

MAE and RMSE are on the log scale (for small errors, proportional errors); MAPE is computed as $100\cdot|\exp(e) - 1|$. To compare methods A and B we compute for each economy the mean difference of absolute errors, $\Delta(i)$ = mean over (T,h) of $[\,|e_A| - |e_B|\,]$, and the average $D = (1/21)\cdot\Sigma\,\Delta(i)$. The sampling distribution of D is obtained by a country-cluster bootstrap: 21 economies are drawn with replacement 4,000 times and the 2.5th and 97.5th percentiles of D are reported. Resampling whole countries preserves the dependence of errors within a country over origins. As a distribution-free check we also use a sign test on the 63 (country, origin) pairs.

Prediction intervals use the empirical quantiles of the shrinkage errors at the same horizon, so that the 80% interval for the actual log stock is

$$[\,\hat{y} - q(0.90)\,,\ \hat{y} - q(0.10)\,] \quad (7)$$

where q(p) is the p-quantile of e. Calibration is assessed leave-one-country-out: quantiles are computed from the other 20 economies and the coverage of the held-out economy's errors is recorded. For h = 3 and 4, which are not evaluated, the h = 2 interval is widened by $\sqrt{(h/2)}$. We also report the interval score [14], $IS = (u - l) + (2/\alpha)\cdot[(l - a)\cdot 1(a < l) + (a - u)\cdot 1(a > u)]$ with $\alpha = 0.2$, where lower is better.

Limitations of the design are explicit. Stocks are nominal, so growth includes inflation and exchange-rate movements; countries use different MSME definitions; and the three origins share common shocks (the 2020 pandemic contraction enters all training windows, and 2022 is a high-inflation year). The bootstrap resamples countries but cannot correct for common time shocks, so the p-values should be read as indicative, not exact. To reduce reliance on the bootstrap we report the results separately by origin (Table 5).

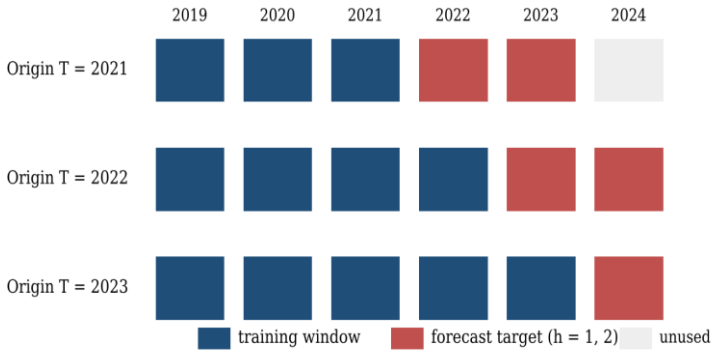


Figure 1. Rolling-origin evaluation design
Source: author. For each origin the model is estimated on the blue years and evaluated on the red years.

Figure 2 plots the indexed series: most economies grow, the dispersion of growth rates is large, and the 2020 contraction of Uzbekistan (−12.7%) is shared by only two other economies, the Philippines and Thailand, whose stocks fell by more.

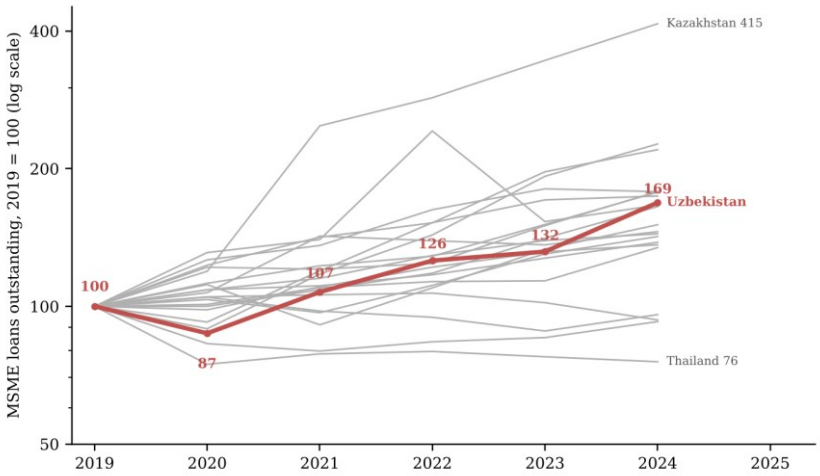


Figure 2. MSME loans outstanding, 2019 = 100, 21 economies
Source: ADB Asia SME Monitor 2025, country Tables x.3; author's calculations.

Figure 3 ranks the 21 economies by mean annual growth: Kazakhstan (32.9%), Tajikistan (17.8%) and Georgia (17.1%) are at the top, Uzbekistan (11.0%) is above the median (8.6%), and Thailand (−5.4%), the Philippines (−1.5%), Singapore (−1.4%) and Samoa (−0.8%) are the only economies with contracting stocks. The whiskers show that year-to-year volatility often exceeds the mean (Papua New Guinea: 10.7% mean, 36.7% SD), which is why country-specific growth estimates are noisy.

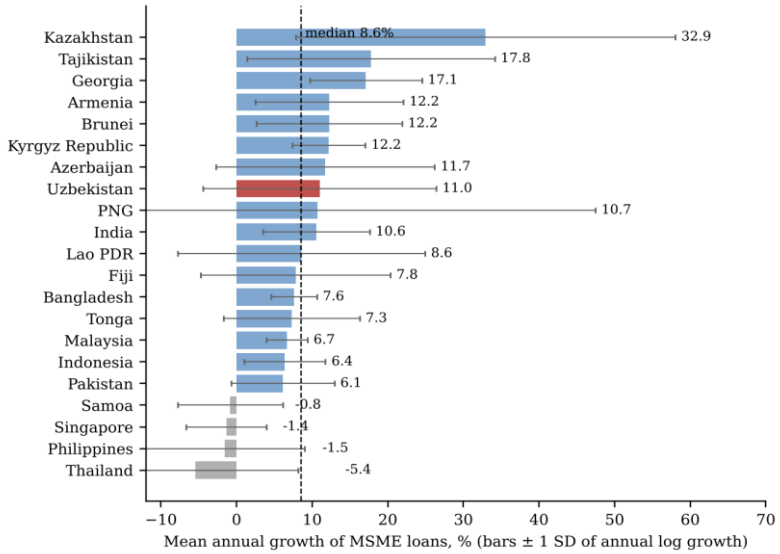


Figure 3. Mean annual growth of MSME loans by economy, 2019–2024 (bars: mean; whiskers: ±1 SD of annual log growth)
Source: ADB Asia SME Monitor 2025, country Tables x.3; author's calculations. Numbers show mean growth in per cent.

3. Results

3.1 Forecast accuracy

Table 2 and Figure 4 show that the two methods that use cross-country information dominate. At h = 1 the shrinkage forecast has the lowest mean absolute log error (0.083), 29% below the random walk (0.117) and 18% below country drift (0.101); pure pooling is almost as good (0.087). The single-country log-trend is the worst method (0.121), which is the formal counterpart of the point that fitting a line to six observations does not forecast well [8]. At h = 2 errors roughly double and the ranking is unchanged; shrinkage and pooling are practically tied (MAE 0.149 versus 0.152, while RMSE favours pooling, 0.186 versus 0.195), so at longer horizons the common component dominates country-specific growth [9].

Table 2. Out-of-sample forecast accuracy (log scale)

Method	n	MAE h=1	RMSE h=1	MAPE h=1, %	MAE / RMSE h=2
Random walk	63	0.117	0.154	11.0	0.210 / 0.248
Country drift	63	0.101	0.149	10.5	0.189 / 0.257
Country log-trend	63	0.121	0.158	12.4	0.197 / 0.256
Pooled growth	63	0.087	0.127	8.6	0.152 / 0.186
Shrinkage (λ = 0.5)	**63**	**0.083**	**0.129**	**8.4**	**0.149 / 0.195**

Source: author's calculations. n = 42 forecasts at h = 2. MAE and RMSE are on log loans.

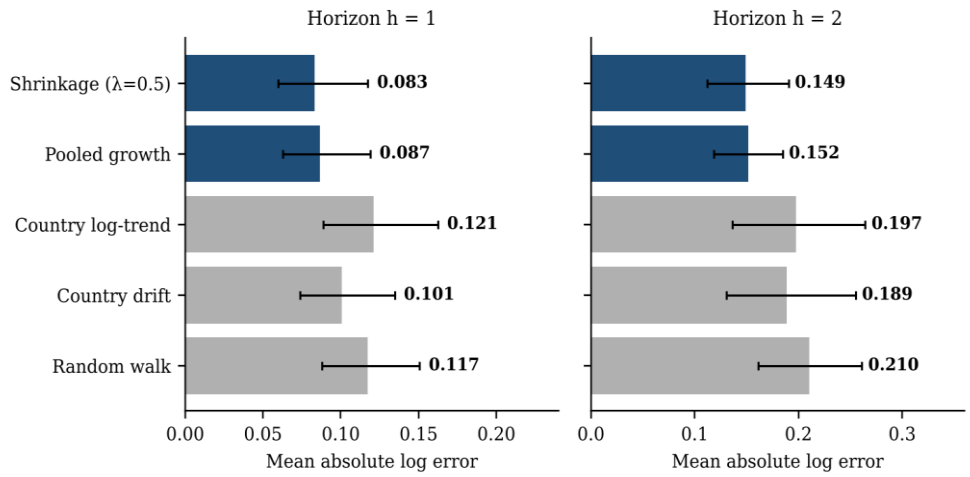


Figure 4. Mean absolute log forecast error by method, with country-cluster bootstrap 95% intervals
Source: author's calculations.

3.2 Statistical comparisons

Table 3 reports mean paired differences in absolute errors. The shrinkage forecast is significantly better than the random walk, drift and trend at both horizons (all bootstrap intervals exclude zero). Pure pooling versus drift is borderline at h = 1 (interval −0.031 to +0.002) and not significant at h = 2. Drift does not significantly beat the random walk (interval −0.003 to +0.036 for naive minus drift), which says that country-specific growth carries little information beyond the last value. At the country level, shrinkage beats the random walk in 17 and drift in 18 of 21 economies at h = 1 [10].

Table 3. Paired differences in mean absolute error (A − B); negative favours A

Comparison (A vs B)	Horizon	Mean difference	Bootstrap 95% interval
Shrinkage vs random walk	1	−0.034	[−0.053, −0.016]
Shrinkage vs country drift	1	−0.018	[−0.034, −0.004]
Shrinkage vs country log-trend	1	−0.038	[−0.062, −0.019]
Pooled vs country drift	1	−0.014	[−0.031, 0.002]
Shrinkage vs random walk	2	−0.061	[−0.106, −0.010]
Shrinkage vs country drift	2	−0.040	[−0.083, −0.005]
Shrinkage vs country log-trend	2	−0.048	[−0.094, −0.009]
Pooled vs country drift	2	−0.037	[−0.091, 0.013]

Source: author's calculations; 4,000 country-cluster bootstrap draws.

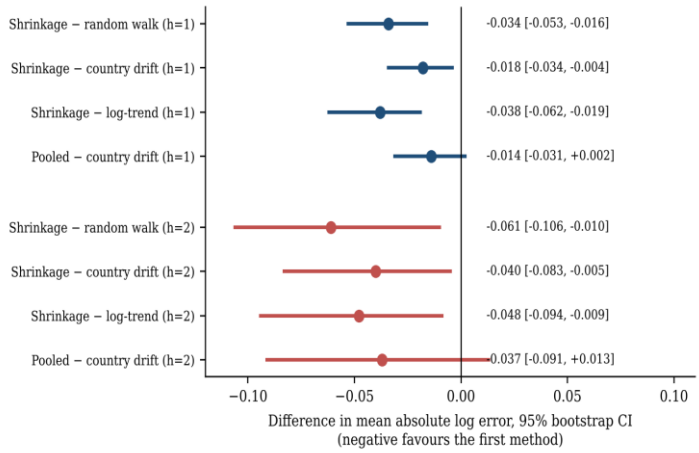


Figure 5. Paired differences in mean absolute log error with 95% bootstrap intervals
Source: author's calculations. Numbers give the mean difference and the interval; an interval that excludes zero indicates a significant difference. Blue: h = 1; red: h = 2.

Table 4 expresses accuracy relative to the random walk. Shrinkage cuts MAE to 71% of the random-walk value at both horizons and has a Theil-type U of 0.84 (h = 1) and 0.79 (h = 2); country drift has U = 0.97 and 1.04, that is, it is no better than the random walk in RMSE terms, and the log-trend is worse (1.03). Figure 6 shows the case-level comparison: shrinkage has the smaller error in 73% of the 63 cases against the random walk (sign test p = 0.0002) and 65% against drift (p = 0.011). At h = 2 the sign test is significant against the random walk (71%, p = 0.004) but not against drift (60%, p = 0.14) or the log-trend (62%, p = 0.08), so evidence of superiority over country-specific methods at two years is weaker than the bootstrap suggests and rests on a few large errors. By origin the mean difference to the random walk is −0.024 (2021), −0.034 (2022) and −0.045 (2023), with shrinkage better in 71–76% of cases each year [11], [12].

Table 4. Accuracy relative to the random walk

Method	Rel. MAE h=1	U (RMSE) h=1	Rel. MAE h=2	U (RMSE) h=2
Country drift	0.86	0.97	0.90	1.04
Country log-trend	1.03	1.03	0.94	1.04
Pooled growth	0.74	0.83	0.72	0.75
Shrinkage (λ = 0.5)	**0.71**	**0.84**	**0.71**	**0.79**

Source: author's calculations. Values below 1 mean better than the random walk.

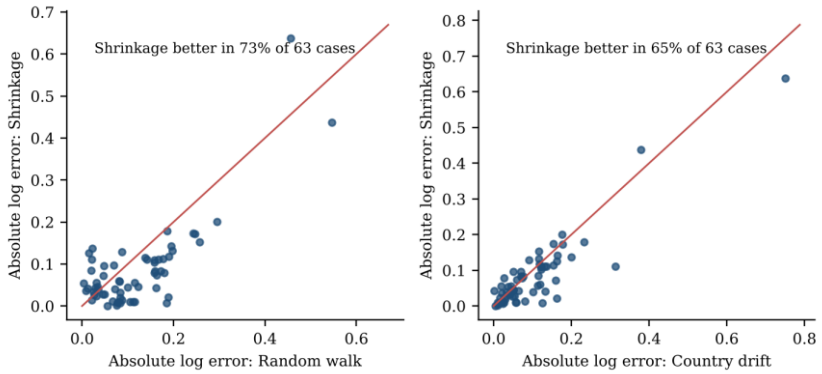


Figure 6. Case-level one-year absolute errors: shrinkage versus random walk and country drift
Source: author's calculations. Points below the 45° line favour shrinkage.

Figure 7 shows where the gains come from. Shrinkage has a smaller error than the random walk in 46 of 63 country–origin cells [13]. The largest gains are in Kazakhstan (−16.7 and −17.7 log points ×100 in 2022 and 2023), Tajikistan (−11.9) and Georgia (−10.4), whose growth was persistently above the benchmark's naive no-change forecast; the largest losses are Papua New Guinea in 2022 (+18.2), Fiji (+11.3 in 2021) and Brunei in 2023 (+11.1), economies with erratic stocks where pooling pulls forecasts in the wrong direction. Gains grow with the length of the training window: the share of cells with improvement is 71% in 2021, 76% in 2022 and 71% in 2023, and the average gain is largest in 2023 (−4.5) [14].

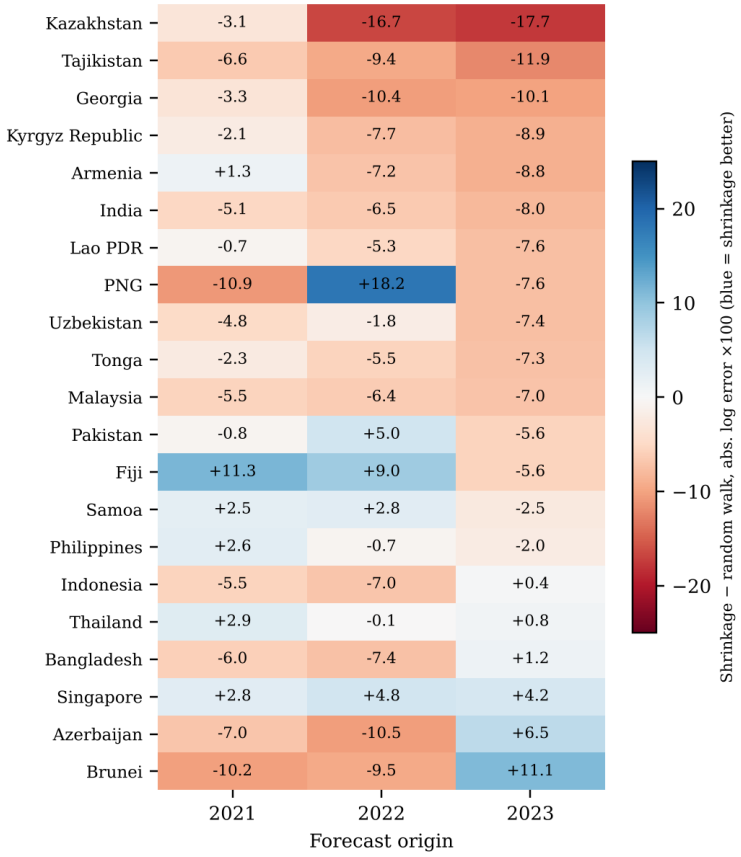


Figure 7. Heat map of the difference in absolute one-year log error, shrinkage minus random walk (×100), by economy and forecast origin

Source: author's calculations. Blue cells: shrinkage is worse; red cells: shrinkage is better.

3.3 Robustness

Table 5 shows that the ordering does not depend on a few observations. Excluding Kazakhstan (whose loan stock jumped from 2.5 to 5.2 trillion tenge in 2021, plausibly a definitional change) leaves shrinkage best (0.085 against 0.096 for drift); excluding Uzbekistan changes nothing (0.082); excluding the three economies with the largest errors (Kazakhstan, Brunei, Papua New Guinea) lowers all errors but retains the ranking [15]. By forecast origin, shrinkage has the lowest or near-lowest error in each year (0.093, 0.097, 0.059). Varying the shrinkage weight shows a shallow optimum: MAE is 0.087 at $\lambda = 0$, 0.081 at 0.25, 0.083 at 0.5, 0.091 at 0.75 and 0.101 at 1, so the fixed $\lambda = 0.5$ is not tuned to the result and the gain does not require a precise weight [16].

Table 5. Robustness of one-year mean absolute log error

Sample	Naive	Drift	Trend	Pooled	Shrink
All 21 economies	0.117	0.101	0.121	0.087	0.083
Excluding Kazakhstan	0.115	0.096	0.115	0.086	0.085

Sample	Naive	Drift	Trend	Pooled	Shrink
Excluding Uzbekistan	0.116	0.100	0.121	0.086	0.082
Excl. Kazakhstan, Brunei, PNG	0.102	0.080	0.100	0.071	0.070
Origin 2021 (n = 21)	0.117	0.114	0.119	0.088	0.093
Origin 2022 (n = 21)	0.132	0.114	0.126	0.109	0.097
Origin 2023 (n = 21)	0.104	0.074	0.118	0.063	0.059

Source: author's calculations. Naive = random walk; Pooled = pooled growth; Shrink = shrinkage with $\lambda = 0.5$.

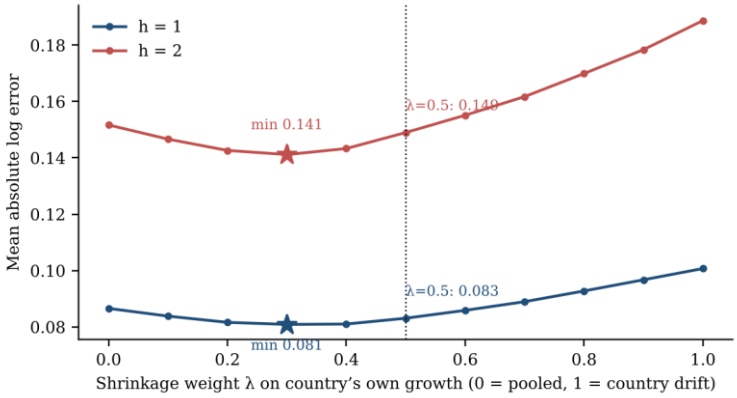


Figure 8. Sensitivity of forecast accuracy to the shrinkage weight λ
Source: author's calculations. Stars mark the minimum of the mean absolute log error on the grid $\lambda = 0, 0.1, \ldots, 1$; the dotted line is the pre-set $\lambda = 0.5$.

Figure 8 shows the full sensitivity curve: the minimum is at $\lambda = 0.3$ for both horizons (0.081 at h = 1 and 0.141 at h = 2), so the pre-set $\lambda = 0.5$ is within 0.002 (h = 1) and 0.008 (h = 2) of the best value.

3.4 Interval calibration

Pooled shrinkage errors have 10th/90th percentiles of −0.140 and +0.097 at h = 1 and −0.218 and +0.148 at h = 2 (log scale; error = forecast minus actual). Applying these intervals leave-one-country-out gives empirical coverage of 76.2% (h = 1) and 78.6% (h = 2) against the nominal 80%, supporting H4 with the caveat that only 63 and 42 errors are available. The lower tail is longer than the upper one, meaning that forecasts more often fall short of realised growth than overshoot it. Figure 9 shows the error distributions [17], [18]. Calibration is not the same as sharpness, however. The mean interval score of the shrinkage-based interval is 0.44 (h = 1) and 0.67 (h = 2), against 0.42 and 0.61 for intervals built in the same way from random-walk errors, because the shrinkage intervals are somewhat wider at h = 1 (0.236 versus 0.219) and miss by more in the tails. The gain of the shrinkage method is therefore in the point forecast; we do not claim that its intervals are sharper than naive ones, only that they are approximately calibrated [19].

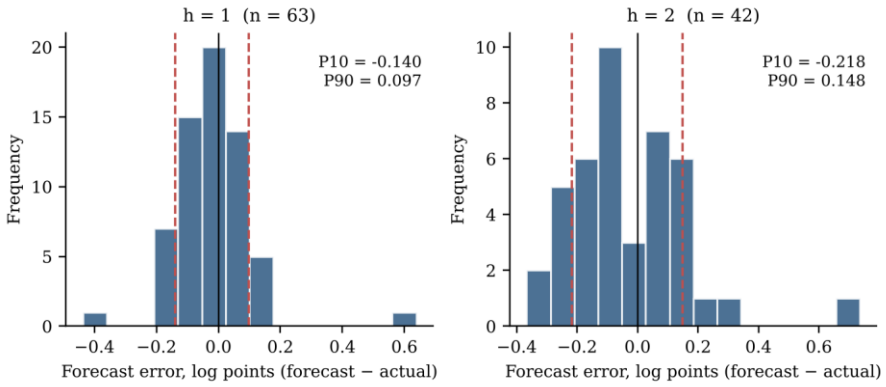


Figure 9. Distribution of shrinkage forecast errors; dashed lines mark the 10th and 90th percentiles
Source: author's calculations.

3.5 Application to Uzbekistan

Uzbekistan's MSME loan stock fell 12.7% in 2020 and then rose 23.1%, 17.2%, 4.6% and 28.0%, reaching 93.4 trillion UZS in 2024; its mean log growth is 10.4% a year against a median of 7.9% for the other 20 economies. The shrinkage forecast is therefore 102.4 trillion UZS in 2025, 112.2 in 2026, 122.9 in 2027 and 134.7 in 2028 (Table 6), a path of 9.6% annual growth. By contrast, extrapolating the country's own log-trend gives 108.9, 122.1 and 136.9 trillion for 2026–2028 while the linear and exponential scenarios of a six-point extrapolation reach 117–186 trillion by 2028. The own-trend point is close to the shrinkage forecast, but its accuracy cannot be assessed on six observations, whereas the shrinkage method has been evaluated; we therefore treat the shrinkage path and interval as the reference.

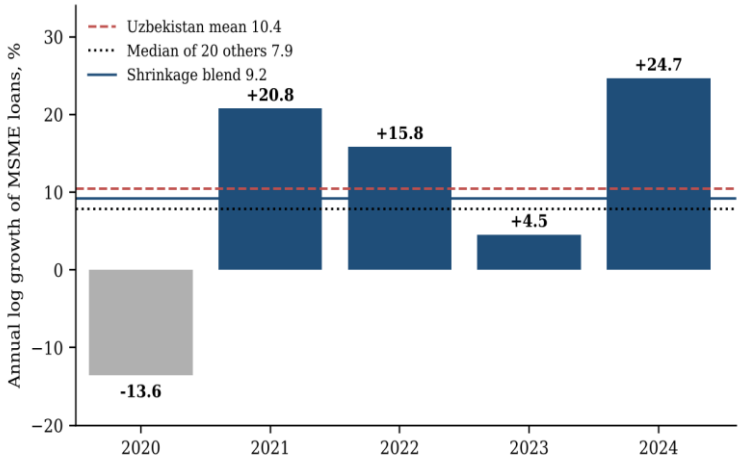


Figure 10. Uzbekistan: annual log growth of MSME loans, 2020–2024, against the cross-country median and the shrinkage blend
Source: ADB Asia SME Monitor 2025, Table 8.3; author's calculations.

Figure 10 shows why shrinkage matters for Uzbekistan: annual growth ranges from −13.6% to +24.7%, so the country mean (10.4%) rests on large swings, and blending it with the cross-country median (7.9%) gives 9.2%.

Worked example (equation 4, h = 1, T = 2024). Uzbekistan's annual log growth rates are −0.136, +0.208, +0.158, +0.045 and +0.247 (2020–2024), so $\bar{g} = 0.1044$. The median of the 20 other economies' $\bar{g}$ is m = 0.0787. With $\lambda = 0.5$ the blended growth is 0.5·0.1044 + 0.5·0.0787 = 0.0916, and $\hat{L}(2025) = 93.425 \cdot \exp(0.0916) = 102.4$ trillion UZS. For h = 4, $\hat{y}$ = y(2024) + 4·0.0916 gives 134.7 trillion. The 80% interval for 2025 is obtained from the h = 1 error quantiles q(0.10) = −0.140 and q(0.90) = +0.097: 93.425·exp(0.0916 − 0.097) = 92.9 and 93.425·exp(0.0916 + 0.140) = 117.8 trillion [20].

Table 6. Forecast of Uzbekistan's MSME loan stock, trillion UZS (ADB definition)

Year	Shrinkage point	80% interval	Country log-trend	Pooled / drift
2025	102.4	92.9 – 117.8	97.1	101.1 / 103.7
2026	112.2	96.7 – 139.6	108.9	109.3 / 115.1
2027	122.9	102.5 – 160.7	122.1	118.3 / 127.8
2028	134.7	109.2 – 183.5	136.9	128.0 / 141.9

Source: author's calculations. Intervals for h = 3–4 widen the h = 2 interval by √(h/2) and are therefore indicative.

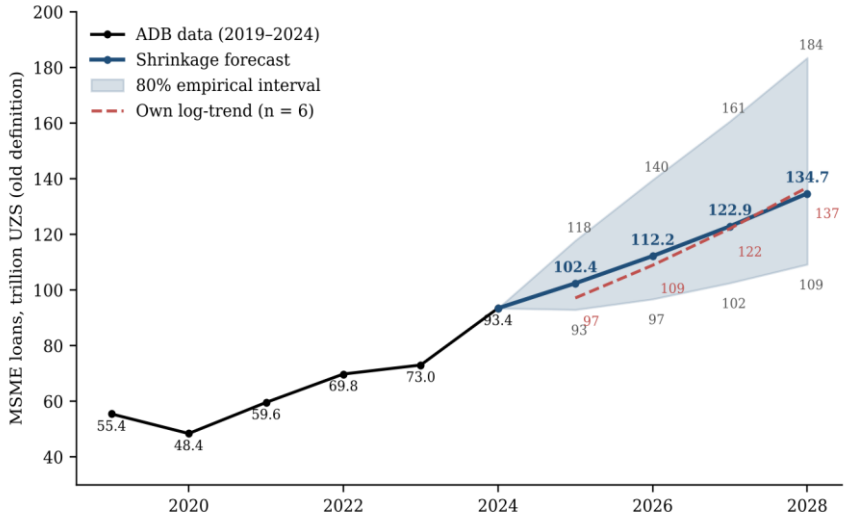


Figure 11. Uzbekistan: MSME loan stock and forecasts with 80% interval, 2019–2028 (numbers in trillion UZS)
Source: ADB Asia SME Monitor 2025, Table 8.3; author's calculations. Bold blue numbers: shrinkage point forecasts; grey: interval bounds; red: own log-trend.

Consistency check. The Central Bank reports that the stock of loans to entrepreneurs rose 8% in 2025 to 384 trillion UZS [10]. This series is on a broader definition (all entrepreneur loans, not the ADB micro-and-small subset), so levels are not comparable; the growth rate, however, lies inside the 80% interval implied by our 2025 forecast (−0.6% to +26% growth). We treat this as a directional check only; the full validation requires ADB's 2025 value, which was not available when this paper was written.

4. Discussion

The main message is methodological: with short panels, partial pooling beats country-specific extrapolation for MSME credit, and the gain comes from shrinking noisy national growth rates, not from a sophisticated model. For Uzbekistan this implies that point projections should be built from a pooled baseline with an explicit interval, and that the 2030 stock targets cited in public statements need to be checked against an interval of this width: the h = 4 interval already spans 109 to 184 trillion UZS.

Limitations. (1) Nominal local-currency stocks: growth contains inflation and depreciation, which differ across countries and years; a real or USD-denominated panel would answer a different question. (2) Definitions are heterogeneous and sometimes change inside a series (Kazakhstan 2021); we show robustness to excluding it but cannot harmonise definitions. (3) Three forecast origins that share common shocks limit effective sample size, and the bootstrap does not remove time dependence. (4) The pooled benchmark uses the median, which is robust but ignores covariates; a hierarchical model with GDP growth, inflation and credit-guarantee programmes could improve it, as could bank-level data. (5) The Uzbek application relies on the old ADB definition; it should be

re-estimated when Central Bank series with a stable MSME definition become long enough [21].

Verdicts on the hypotheses. H1 is supported: pooled growth beats country drift and log-trend at h = 1, although the pooled-versus-drift interval just touches zero (−0.031 to +0.002). H2 is supported: shrinkage has the lowest MAE at h = 1 and is significantly better than all country-specific methods. H3 is partly supported: the gain over the random walk persists at h = 2, but against country drift and log-trend the sign tests are not significant (p = 0.14 and 0.08), and only the bootstrap indicates a significant gain. H4 is supported for calibration (coverage 76–79% against 80%) but not for sharpness, since the interval score is not better than that of random-walk intervals [22].

5. Conclusion

Using 21 economies and 105 out-of-sample forecasts, we find that shrinking country growth toward the cross-country median reduces one-year log errors by 18% relative to country drift and 29% relative to a random walk, that a single-country log-trend is the least accurate approach, and that cross-country errors yield approximately calibrated prediction intervals. For Uzbekistan the evaluated method gives 134.7 trillion UZS in 2028 (80% interval 109.2–183.5), which is close to the country's own log-trend (136.9) but, unlike it, comes with an interval whose width has been checked out of sample. Future research should extend the panel with bank-level data and harmonised definitions, test hierarchical Bayesian and covariate-augmented models, and evaluate forecasts at monthly frequency, where central-bank data are available.

Author contributions (CRediT): [to be completed by the author]. Funding: [to be completed]. Conflict of interest: [to be completed]. Use of AI tools: [to be completed according to the journal policy]. Data availability: the panel, forecast errors and the Python code to reproduce all tables and figures are provided as supplementary files (msme_panel.csv, fc_errors.csv, fc.py, fc2.py, fc3.py, figs_fq.py, figs_fq2.py).

Appendix A. Data panel

Table A1. MSME loans outstanding, 21 economies, 2019 and 2024 (local currency, units as reported)

Economy	Unit	2019	2024	Mean growth, %	SD of growth, %
Armenia	AMD mn	970,394	1,729,306	12.2	9.8
Azerbaijan	AZN mn	3,725	6,490	11.7	14.5
Georgia	GEL mn	8,121	17,870	17.1	7.4
Kazakhstan	KZT mn	2,108,945	8,746,480	32.9	25.1
Kyrgyz Rep.	KGS mn	113,900	202,322	12.2	4.8
Tajikistan	TJS mn	1,284	2,907	17.8	16.4
Uzbekistan	UZS mn	55,430,003	93,424,800	11.0	15.4
Bangladesh	BDT mn	2,091,795	3,013,000	7.6	3.0
India	INR mn	16,980,402	28,049,052	10.6	7.0
Pakistan	PKR mn	477,232	641,337	6.1	6.8
Brunei	BND	8,996,023	16,022,670	12.2	9.6
Indonesia	IDR bn	1,107,509	1,509,419	6.4	5.4
Lao PDR	LAK bn	14,104	21,267	8.6	16.4
Malaysia	MYR mn	303,032	418,207	6.7	2.7
Philippines	PHP mn	588,837	545,193	-1.5	10.6
Singapore	SGD mn	86,242	80,539	-1.4	5.3
Thailand	THB bn	6,581	4,978	-5.4	13.6

Economy	Unit	2019	2024	Mean growth, %	SD of growth, %
Fiji	FJD mn	618	900	7.8	12.5
PNG	PGK mn	3,161	5,262	10.7	36.7
Samoa	WST mn	633	607	-0.8	6.9
Tonga	TOP 000s	165,454	235,050	7.3	9.0

Source: ADB Asia SME Monitor 2025, country Tables x.3; author's calculations. Mean growth = exp(mean log growth) − 1; SD = standard deviation of annual log growth (×100).

REFERENCES

[1] A. N. Berger and G. F. Udell, 'A more complete conceptual framework for SME finance', *J. Bank. Finance*, vol. 30, no. 11, pp. 2945–2966, 2006.

[2] Central Bank of the Republic of Uzbekistan, 'Annual report 2025', Central Bank of the Republic of Uzbekistan, Tashkent, 2026.

[3] R. J. Hyndman and A. B. Koehler, 'Another look at measures of forecast accuracy', *Int. J. Forecast.*, vol. 22, no. 4, pp. 679–688, 2006.

[4] T. E. Clark and K. D. West, 'Approximately normal tests for equal predictive accuracy in nested models', *J. Econom.*, vol. 138, no. 1, pp. 291–311, 2007.

[5] Asian Development Bank, 'Asia Small and Medium-Sized Enterprise Monitor 2025', ADB, Manila, 2025.

[6] J. H. Stock and M. W. Watson, 'Combination forecasts of output growth in a seven-country data set', *J. Forecast.*, vol. 23, no. 6, pp. 405–430, 2004.

[7] J. E. Stiglitz and A. Weiss, 'Credit rationing in markets with imperfect information', *Am. Econ. Rev.*, vol. 71, no. 3, pp. 393–410, 1981.

[8] B. Efron and C. Morris, 'Data analysis using Stein's estimator and its generalizations', *J. Am. Stat. Assoc.*, vol. 70, no. 350, pp. 311–319, 1975.

[9] G. S. Maddala, R. P. Trost, H. Li, and F. Joutz, 'Estimation of short-run and long-run elasticities of energy demand from panel data using shrinkage estimators', *J. Bus. Econ. Stat.*, vol. 15, no. 1, pp. 90–100, 1997.

[10] R. G. King and R. Levine, 'Finance and growth: Schumpeter might be right', *Q. J. Econ.*, vol. 108, no. 3, pp. 717–737, 1993.

[11] R. Levine, 'Finance and growth: Theory and evidence', in *Handbook of Economic Growth*, vol. 1A, P. Aghion and S. Durlauf, Eds, Amsterdam: Elsevier, 2005, pp. 865–934.

[12] R. G. Rajan and L. Zingales, 'Financial dependence and growth', *Am. Econ. Rev.*, vol. 88, no. 3, pp. 559–586, 1998.

[13] T. Beck, A. Demirgüç-Kunt, and V. Maksimovic, 'Financing patterns around the world: Are small firms different?', *J. Financ. Econ.*, vol. 89, no. 3, pp. 467–487, 2008.

[14] M. P. Clements and D. F. Hendry, *Forecasting Economic Time Series*. Cambridge: Cambridge University Press, 1998.

[15] A. N. Berger and G. F. Udell, 'Relationship lending and lines of credit in small firm finance', *J. Bus.*, vol. 68, no. 3, pp. 351–381, 1995.

[16] T. Beck and A. Demirgüç-Kunt, 'Small and medium-size enterprises: Access to finance as a growth constraint', *J. Bank. Finance*, vol. 30, no. 11, pp. 2931–2943, 2006.

[17] T. Beck, A. Demirgüç-Kunt, and R. Levine, 'SMEs, growth, and poverty: Cross-country evidence', *J. Econ. Growth*, vol. 10, no. 3, pp. 199–229, 2005.

[18] T. Gneiting and A. E. Raftery, 'Strictly proper scoring rules, prediction, and estimation', *J. Am. Stat. Assoc.*, vol. 102, no. 477, pp. 359–378, 2007.

[19] M. A. Petersen and R. G. Rajan, 'The benefits of lending relationships: Evidence from small business data', *J. Finance*, vol. 49, no. 1, pp. 3–37, 1994.

[20] J. M. Bates and C. W. J. Granger, 'The combination of forecasts', *Oper. Res. Q.*, vol. 20, no. 4, pp. 451–468, 1969.

[21] A. N. Berger and G. F. Udell, 'The economics of small business finance: The roles of private equity and debt markets in the financial growth cycle', *J. Bank. Finance*, vol. 22, no. 6–8, pp. 613–673, 1998.

[22] B. H. Baltagi, J. M. Griffin, and W. Xiong, 'To pool or not to pool: Homogeneous versus heterogeneous estimators applied to cigarette demand', *Rev. Econ. Stat.*, vol. 82, no. 1, pp. 117–126, 2000.