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Article

Improving the Forecasting of Budget Revenues by Tax Type

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Abstract: *This article examines how budget revenue forecasting can be improved by modeling individual tax categories rather than relying primarily on aggregate revenue projections. Using official budget execution data for Uzbekistan for 2020–2025, the study analyzes corporate income tax, personal income tax, turnover tax, value added tax, excise tax, customs duty, property tax, land tax, subsoil use tax, and water use tax. Three transparent benchmark methods—linear trend extrapolation, compound annual growth, and median year-on-year growth—are assessed through rolling-origin validation. The exercise shows that forecast performance differs materially across taxes because tax bases, payment schedules, administrative changes, commodity exposure, and policy adjustments are heterogeneous. The paper therefore proposes a tax-specific forecasting architecture in which statistical models are selected by out-of-sample error, then supplemented by explicit tax-base assumptions, policy-costing adjustments, scenario ranges, and continuous forecast-error monitoring. The proposed framework is designed to improve both technical accuracy and the transparency of fiscal planning.*

Keywords: *budget revenue, tax revenue, forecasting, value added tax, corporate income tax, time series, forecast error, fiscal planning.*

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1. Introduction

Reliable revenue forecasts are a core input into the annual budget process because expenditure ceilings, deficit targets, financing needs, and the credibility of medium-term fiscal plans all depend on the expected resource envelope. Forecasting errors are not neutral. Persistent overestimation may create financing gaps and force expenditure compression during the fiscal year, while systematic underestimation can weaken the usefulness of the budget as a policy instrument. Earlier international evidence has also shown that tax-revenue forecasts may contain sizeable errors when they rely heavily on judgment, simple extrapolation, or macroeconomic assumptions that do not adequately reflect the behavior of individual tax bases [1]

The problem becomes more important when the tax system is structurally heterogeneous. Value added tax is linked to consumption, imports, refund mechanisms, and compliance. Corporate income tax responds to profitability, loss carry-forwards, advance-payment rules, commodity prices, and the concentration of large taxpayers. Personal income tax is closely connected with the wage bill and formal employment, whereas customs duties depend on import volumes, tariff policy, exchange-rate movements, and trade composition. Resource taxes can be highly sensitive to production volumes and world commodity prices. For this reason, a single aggregate growth

coefficient applied to total revenue may appear convenient but can mask the mechanisms that actually generate receipts.[2]

Uzbekistan provides a useful case for examining this issue because the structure of state budget revenue has changed rapidly in recent years, while tax administration, VAT procedures, the tax base, and the distribution of revenues across budget levels have continued to evolve. Official data show that state budget revenue increased from UZS 132.9 trillion in 2020 to UZS 359.8 trillion in 2025. Over the same period, the behavior of separate tax categories differed substantially. For example, VAT receipts rose from UZS 31.2 trillion to UZS 76.0 trillion, while corporate income tax increased from UZS 28.7 trillion to UZS 72.3 trillion. Such differences make disaggregated forecasting economically meaningful rather than merely a statistical refinement.

The purpose of this study is to develop a practical framework for improving budget-revenue forecasts by tax type. The article has three objectives: first, to evaluate the dynamics of the main tax categories over 2020–2025; second, to compare several transparent benchmark forecasting methods using out-of-sample validation; and third, to formulate an operational forecasting architecture that combines statistical performance with tax-base information, policy adjustments, and scenario analysis. The emphasis is deliberately placed on methods that can be reproduced in common analytical software and audited by fiscal institutions.[3].

2. Materials And Methods

The international literature treats revenue forecasting as a two-stage process in which macroeconomic projections are translated into expected tax receipts through assumptions about the relevant tax bases, elasticities, effective tax rates, and policy parameters. IMF guidance emphasizes that trend extrapolation is useful as a benchmark but is less reliable when tax bases or tax legislation change materially. A more robust approach links individual taxes to the economic variables on which they are levied and makes policy effects explicit. Recent IMF work on corporate income tax forecasting similarly stresses the difficulty of forecasting highly volatile receipts and recommends parsimonious empirical specifications when sufficient data are available, while retaining simple benchmarks for comparison [4]

Forecast evaluation is equally important. Hyndman and Athanasopoulos argue that model selection should be based on out-of-sample forecast performance rather than goodness of fit alone. This principle is particularly relevant for fiscal forecasting because a model can reproduce historical data well and still produce poor budget-year estimates. The present study therefore uses rolling-origin validation: the forecasting model is re-estimated using only information that would have been available before each forecast year, and the resulting prediction is compared with the actual outcome.

The empirical database consists of annual state budget receipts by tax type published by the Ministry of Economy and Finance of the Republic of Uzbekistan for 2020–2025. Ten revenue categories with consistent annual observations were retained: corporate income tax, personal income tax, turnover tax, VAT, excise tax, customs duty, property tax, land tax, subsoil use tax, and water use tax. The values are expressed in trillion UZS. These data are used only for methodological evaluation; forecasts reported in the article are author calculations and should not be interpreted as official government projections.[5]

Three benchmark models are compared. The first is a linear trend model, $R_t = a + bt + \varepsilon_t$, which assumes a stable absolute increase in revenue. The second is a compound annual growth model, $R_{(t+1)} = R_t(1+g)$, where g is the compound annual growth rate calculated from the available historical sample. The third applies the median of observed year-on-year growth rates, which is less sensitive than the arithmetic mean to one-off spikes. For each tax type, forecasts are evaluated over successive origins for 2023, 2024, and 2025. The main accuracy criterion is mean absolute percentage error (MAPE): MAPE

= (1/n) Σ |(A_t − F_t)/A_t| × 100, where A_t denotes actual revenue and F_t denotes the forecast.

The Figure 1. method is intentionally parsimonious. With only six annual observations per tax category, complex machine-learning specifications would create a serious risk of overfitting and false precision. The appropriate methodological conclusion is therefore not that simple models are universally superior, but that annual data alone are insufficient for high-dimensional models. In an operational forecasting system, the same framework should be re-estimated using monthly or quarterly receipts together with macroeconomic drivers such as nominal consumption, imports, wage bill, corporate profits, commodity prices, exchange rates, and sectoral output.[6]

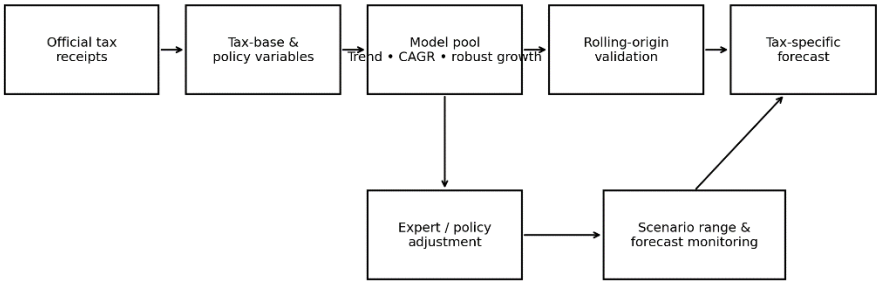


Figure 1. Proposed tax-specific revenue forecasting framework
Source: developed by the author.

3. Results

The first result is the strong expansion of the major tax bases in nominal terms, combined with marked differences in growth paths across taxes. The ten selected tax categories generated approximately UZS 112.9 trillion in 2020 and UZS 272.4 trillion in 2025. This represents a 141 percent cumulative increase over five years. However, the aggregate figure 2. hides substantial heterogeneity. Corporate income tax, VAT, personal income tax, and subsoil use tax accounted for the largest shares of the selected taxes in 2025, whereas turnover and water-use taxes remained comparatively small.[7]

Table 1. State budget receipts by selected tax type, 2020–2025 (trillion UZS)[8]

Tax type	2020	2021	2022	2023	2024	2025
Corporate income tax	28.71	38.36	37.65	40.78	52.62	72.30
Personal income tax	15.14	18.92	24.28	29.92	35.38	42.44
Turnover tax	1.35	1.65	2.51	2.41	2.83	3.07
VAT	31.18	38.44	52.19	57.89	59.28	76.03
Excise tax	11.70	13.09	13.46	15.83	19.06	21.86
Customs duty	3.55	4.76	5.75	9.61	10.00	11.75
Property tax	1.97	2.46	4.02	5.10	6.81	8.01
Land tax	2.39	4.08	5.31	6.89	8.22	10.04
Subsoil use tax	16.42	15.81	13.89	15.30	20.17	25.83
Water use tax	0.48	0.68	0.70	0.79	1.17	1.07

Source: compiled from the Ministry of Economy and Finance of the Republic of Uzbekistan, state budget revenue execution data for 2020–2025.

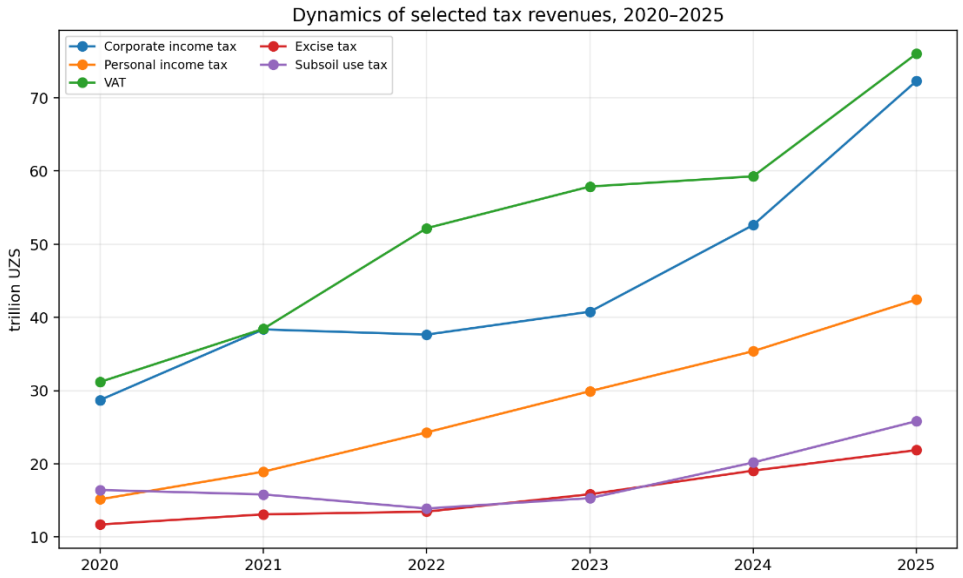


Figure 2. Dynamics of selected major tax revenues, 2020–2025

Source: author calculations based on official budget execution data.

The trajectories in Figure 2 support the case for differentiated models. Personal income tax displays a comparatively smooth upward path, making growth-based forecasting relatively stable. Corporate income tax is more volatile: receipts weakened slightly in 2022, then accelerated sharply in 2024–2025. VAT also shows periods of rapid expansion followed by slower growth, reflecting both tax-base dynamics and changes in administration and refund arrangements. Subsoil-use tax is even more cyclical, with a decline between 2020 and 2022 followed by a pronounced recovery. Figure 3. Treating these series as if they shared one common growth process would therefore increase model risk.[9]

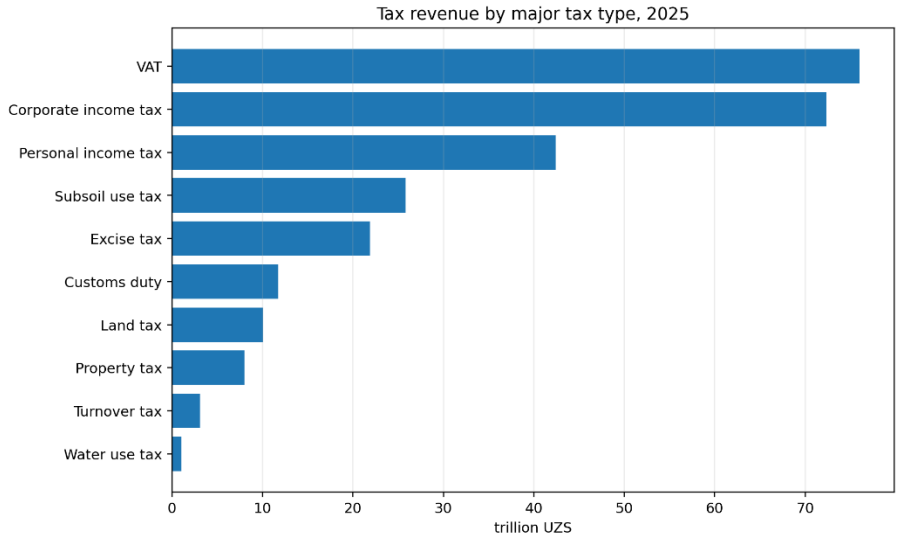


Figure 3. Composition of selected tax revenues in 2025

Source: author calculations based on official budget execution data.

The rolling-origin validation confirms that no single benchmark dominates across all taxes. Median year-on-year growth performs well for personal income tax and excise tax, where the direction of growth is relatively persistent but individual annual rates still vary. Linear trend performs better for VAT, turnover tax, customs duty, property tax, land tax, and water-use tax in the selected validation window. Table 2. Compound annual growth produces the lowest average error for corporate income tax and subsoil-use tax, although both remain comparatively difficult to forecast.[10]

Table 2. Tax-specific model selection and validation results

Tax type	Selected benchmark	Rolling MAPE, %	2026 model estimate, trn UZS
Corporate income tax	CAGR	11.31	86.97
Personal income tax	Median growth	3.97	52.28
Turnover tax	Linear trend	12.14	3.50
VAT	Linear trend	9.70	81.75
Excise tax	Median growth	5.30	25.08
Customs duty	Linear trend	12.67	13.62
Property tax	Linear trend	5.99	9.16
Land tax	Linear trend	1.85	11.38
Subsoil use tax	CAGR	20.07	28.28
Water use tax	Linear trend	14.60	1.27

Note: MAPE is calculated from rolling one-step-ahead forecasts for 2023–2025. The 2026 values are statistical estimates produced from 2020–2025 data and are not official forecasts.

The error distribution is as important as the point forecasts. Land tax exhibits the lowest average MAPE in this simple exercise, while subsoil-use tax has the highest. The implication is straightforward: forecast governance should be proportional to uncertainty. Stable taxes can be forecast with relatively narrow intervals and lighter expert intervention. Volatile taxes should receive explicit scenario bands, commodity-price assumptions where relevant, and more frequent within-year updating. For corporate income tax, the sharp rise in 2025 also warns against mechanically extrapolating a single exceptional growth rate into the future.[11]

A second useful finding comes from the difference between the approved 2025 state budget revenue plan and the actual outcome. The 2025 plan envisaged state budget revenue of approximately UZS 308.5 trillion, whereas the reported annual execution reached UZS 359.8 trillion. The gap illustrates why forecast systems must include systematic post-budget updating. A forecast prepared late in the preceding year cannot incorporate all subsequent information on actual collections, nominal economic activity, taxpayer profitability, imports, administrative measures, and policy implementation. The appropriate response is not to replace the annual budget forecast, but to maintain a sequence of technical updates during the year and transparently reconcile them with the original plan.

4. Discussion

The empirical results support a shift from aggregate revenue forecasting toward a modular system organized by tax type. The central weakness of an aggregate approach is not simply lower statistical sophistication. It is the loss of economic interpretation. If total revenue is forecast as a fixed share of GDP or by a single trend, the analyst cannot clearly distinguish whether a deviation is caused by household consumption, corporate profits, imports, wage growth, mining output, tax refunds, legislative changes, or compliance. Disaggregation makes the forecast explainable and therefore easier to challenge, update, and audit.[12]

The proposed system should have four layers. The first layer is a statistical baseline for each major tax. For high-frequency series, this can include exponential smoothing, ARIMA, state-space models, and parsimonious regression specifications. The second layer links each tax to its economic base: VAT to taxable consumption and imports; personal income tax to the formal wage bill; corporate income tax to taxable profits and sectoral profitability; customs duty to dutiable imports and tariff structure; and resource taxes to production quantities, prices, and sector-specific tax parameters. The third layer applies explicit policy adjustments for rate changes, exemptions, thresholds, refund rules,

payment schedules, and administrative reforms. The fourth layer combines baseline and policy effects into alternative macro-fiscal scenarios.[13]

Forecasting institutions should also separate model error from policy error. A statistical model may perform well under unchanged legislation and still miss the budget outcome because a tax reform was introduced after the estimation period. Conversely, a correct policy costing can be undermined by an inaccurate macroeconomic base. Maintaining an error-decomposition table after each budget year would allow analysts to identify whether the main source of deviation was the macro forecast, tax-base elasticity, implementation timing, compliance, or discretionary policy.

For Uzbekistan, improving the data frequency is likely to yield larger benefits than immediately moving to highly complex algorithms. Monthly receipts by tax type, refunds, arrears, taxpayer groups, and large-taxpayer concentration should be integrated with monthly or quarterly macroeconomic indicators. This would expand the effective sample size and permit real-time models. Machine-learning methods may then be used as challenger models, but they should not replace transparent benchmarks unless they demonstrate stable out-of-sample gains and remain interpretable enough for fiscal decision-making.[14]

The results also suggest introducing forecast ranges rather than presenting only one number. A central estimate can be accompanied by optimistic and adverse scenarios generated from macroeconomic assumptions and historical forecast errors. For taxes with commodity exposure or concentrated taxpayer bases, fan charts or confidence intervals can communicate uncertainty more honestly than a single precise figure. This is particularly important when budget expenditure commitments are difficult to reverse.

Several limitations should be acknowledged. The empirical exercise uses annual data and a short sample, so the numerical rankings of the benchmark models should not be treated as permanent. Structural reforms, inflation, and changes in tax administration also affect nominal receipts and may distort simple trends. The study therefore demonstrates a forecasting architecture rather than claiming that the reported 2026 model estimates are definitive. A stronger applied extension would use monthly data, separate tax and customs collection components, incorporate macroeconomic bases, and estimate policy-adjusted elasticities.[15].

5. Conclusion

Improving budget revenue forecasting requires more than choosing a more sophisticated mathematical model. The principal improvement is to organize the forecasting process around the economic and administrative characteristics of individual taxes. Evidence from Uzbekistan's 2020–2025 budget execution data shows materially different growth patterns and forecast errors across corporate income tax, personal income tax, VAT, excise, customs, property and resource taxes. This heterogeneity makes tax-specific modeling preferable to the mechanical extrapolation of total revenue.

A practical forecasting system should therefore combine four elements: transparent statistical benchmarks, tax-base indicators, explicit policy adjustments, and continuous out-of-sample evaluation. Models should be selected according to forecast performance rather than in-sample fit, and volatile taxes should be accompanied by wider scenario ranges and more frequent revisions. The annual budget forecast should become the starting point of a monitored forecasting cycle rather than a fixed number that remains unchanged throughout the fiscal year.

The proposed framework is feasible with existing analytical tools and can be implemented progressively. The immediate priority is to standardize monthly tax-type datasets and forecast-error reporting. Once a sufficiently long and consistent database is available, econometric and machine-learning challenger models can be introduced without sacrificing transparency. In this way, forecasting becomes not only more accurate, but also more explainable, auditable, and useful for medium-term fiscal management.

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