

Statistical Analysis as a Tool for Assessing and Forecasting Economic Processes

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Abstract. This article examines how statistical analysis supports the assessment and forecasting of economic processes and demonstrates why data definitions, revisions, and uncertainty must accompany numerical results. The study combines conceptual analysis with an illustrative case study of Georgia. Official annual unemployment data for 2021–2025, population releases, demographic indicators, and the Economic Analysis Portal of the National Statistics Office of Georgia are examined alongside methodological literature on descriptive statistics, econometrics, forecasting, and official data quality. The results show that Georgia's unemployment rate fell from 20.6 percent in 2021 to 13.9 percent in 2025, but the decline was uneven and stopped in the final year. A linear time-trend fitted to only five observations yields a 2026 point estimate of 11.38 percent and a wide 95 percent prediction interval of 6.99–15.77 percent; it is therefore presented as a diagnostic benchmark, not a policy forecast. The population case reveals an additional risk: revisions following the 2024 census materially changed the historical series, making unrevised figures unsuitable for simple extrapolation. The article concludes that credible economic assessment requires reproducible calculations, metadata, revision awareness, alternative scenarios, and explicit communication of uncertainty.

Keywords: statistical analysis, economic forecasting, unemployment, data revision, time series, official statistics, Georgia

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İqtisadi proseslərin qiymətləndirilməsi və proqnozlaşdırılması vasitəsi kimi statistik təhlil

Nanuli Xizanişvili 

Xülasə. Məqalədə statistik təhlilin iqtisadi proseslərin qiymətləndirilməsi və proqnozlaşdırılmasına necə xidmət etdiyi araşdırılır, rəqəmsal nəticələrlə yanaşı məlumat təriflərinin, düzəlişlərin və qeyri-müəyyənliyin göstərilməsinin zəruriliyi əsaslandırılır. Tədqiqat konseptual təhlili Gürcüstan üzrə nümunəvi hadisə araşdırması ilə birləşdirir. Gürcüstan Milli Statistika Xidmətinin 2021–2025-ci illər üzrə rəsmi işsizlik göstəriciləri, əhali məlumatları, demoqrafik göstəricilər və İqtisadi Təhlil Portalı təsviri statistika, ekonometrika, proqnozlaşdırma və rəsmi statistikanın keyfiyyəti üzrə metodoloji ədəbiyyatla birlikdə təhlil edilmişdir. Nəticələr göstərir ki, işsizlik səviyyəsi 2021-ci ildəki 20,6 faizdən 2025-ci ildə 13,9 faizə enmiş, lakin azalma qeyri-bərabər olmuş və son ildə dayanmışdır. Beş müşahidəyə uyğunlaşdırılan xətti trend 2026-cı il üçün 11,38 faiz nöqtə qiyməti və 6,99–15,77 faiz geniş proqnoz intervalı verir; buna görə nəticə siyasət proqnozu deyil, diaqnostik meyar kimi şərh

olunur. Əhali nümunəsi göstərir ki, 2024-cü il siyahıyaalmasından sonrakı düzəlişlər tarixi sıranı əhəmiyyətli dərəcədə dəyişmişdir. Etibarlı qiymətləndirmə təkrarlana bilən hesablamalar, metadata, düzəlişlərin izlənməsi, alternativ ssenarilər və qeyri-müəyyənliyin açıq təqdim edilməsini tələb edir.

Açar sözlər: statistik təhlil, iqtisadi proqnozlaşdırma, işsizlik, məlumatların düzəlişi, zaman sırası, rəsmi statistika, Gürcüstan

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Introduction

Economic decisions depend on claims about the present and expectations about the future. Governments evaluate employment, inflation, investment, output, and demographic change; firms assess demand, costs, labour availability, and risk. Statistical analysis makes these processes observable by converting records and surveys into indicators, comparisons, and models. Its value, however, does not come from calculation alone. A result is useful only when the underlying concept is defined, the data source is appropriate, the method is reproducible, and uncertainty is communicated.

Descriptive statistics summarize the level, distribution, and change of economic variables. Index numbers permit comparison of prices or quantities across time. Correlation and regression describe relationships, while time-series methods use temporal structure to construct forecasts. These tools answer different questions and cannot be substituted for one another. A trend may describe movement without identifying its cause, and a strong fitted relationship may still forecast poorly outside the observed period (Shmueli, 2010; Wooldridge, 2020).

Forecasting adds a further burden. A point estimate compresses assumptions about the data-generating process into one number. If those assumptions are hidden, users may interpret a conditional model output as a certain future outcome. Forecasting practice therefore requires benchmarks, residual diagnostics, prediction intervals, and comparison with alternative specifications (Chatfield, 2000; Hyndman & Athanasopoulos, 2021). Complex methods do not automatically solve the problem; model performance depends on the structure, size, and stability of the data (Makridakis et al., 2018).

Official statistics require particular care because published series can be revised. Benchmark revisions, revised classifications, updated seasonal factors, survey redesign, and population censuses can alter earlier observations. The Fundamental Principles of Official Statistics emphasize professional standards, scientific methods, transparency, and public access to explanatory information (United Nations, 2014). The European Statistics Code of Practice likewise connects quality with accessibility, coherence, comparability, and clear documentation (Eurostat, 2017).

Georgia provides a useful illustrative case because the National Statistics Office of Georgia publishes labour-market and demographic data together with interactive analytical services. A superficial reading of these figures can suggest a smooth decline in unemployment and population. Yet several values commonly repeated in such summaries belong to a different reference year or have been superseded by revised data. This problem demonstrates a central methodological point: data vintage and metadata are part of the result.

The study asks three questions. First, what analytical sequence connects official data with defensible economic assessment? Second, what can a short unemployment series support in relation to a 2026 forecast? Third, how do revisions to population estimates affect interpretation? The objective is to preserve the article's applied focus while replacing unsupported extrapolation with a transparent and reproducible framework.

Materials and Methods

The study uses a qualitative review of statistical methodology and an illustrative quantitative case study. The conceptual component distinguishes description, explanation, and prediction. The empirical component uses annual unemployment rates for Georgia from 2021 through 2025 and published population estimates for 2025 and 2026. All empirical values come from the National Statistics Office of Georgia. The employment series reports 20.6, 17.3, 16.4, 13.9, and 13.9 percent for 2021-2025 respectively (National Statistics Office of Georgia, 2026a).

The population analysis compares two data vintages. A release dated 25 April 2025 reported 3,704.5 thousand residents as of 1 January 2025 and stated that the estimate excluded occupied territories (National Statistics Office of Georgia, 2025). The current population database, accessed on 14 September 2026, reports a revised value of 3,930.4 thousand for 2025 and 3,941.1 thousand for 2026 (National Statistics Office of Georgia, 2026b). The difference is treated as a revision issue rather than as real population growth between two observations bearing the same reference date.

For unemployment, the analysis calculates annual percentage-point changes, the arithmetic mean, and the average annual change between the first and last observations. A simple ordinary least squares model is fitted for demonstration: $y_t = a + bt + e_t$, where y_t is the annual unemployment rate and t is the calendar year. The fitted slope, coefficient of determination, 2026 point forecast, and a 95 percent prediction interval are reported.

The model is intentionally simple. Its purpose is to show what a transparent baseline can and cannot establish. Five annual observations are insufficient for a robust structural forecast, do not permit testing of seasonality, and cannot isolate causal effects. The prediction interval is calculated for a new observation, not merely for the mean fitted response. This distinction makes the reported uncertainty wider and more relevant to forecasting.

The demographic component does not fit a trend across the revised population series because the census-related break compromises comparability. Instead, it applies a data-quality checklist: reference period, territorial coverage, unit of measurement, publication date, revision status, and comparability with earlier releases. Live-birth totals for 2024 and 2025 are used only as an additional descriptive indicator; they are not treated as proof of a single causal mechanism (National Statistics Office of Georgia, 2026b).

The article also reviews the Economic Analysis Portal as a dissemination tool. The portal permits users to examine sectoral value added, employment, and compensation of employees under alternative settings (National Statistics Office of Georgia, n.d.). The review concerns its analytical function, not a usability experiment. No interviews, surveys, personal data, or confidential records were used.

Results

The first result is a five-step sequence for applied economic analysis. The analyst should define the economic concept, inspect the source and metadata, describe the observed pattern, select a model appropriate to the question, and communicate uncertainty and revision status. Skipping the first two steps can produce a precise calculation for the wrong quantity. Skipping the final step can turn a conditional estimate into an apparently certain claim.

The unemployment series shows a substantial but uneven improvement. The rate fell by 6.7 percentage points between 2021 and 2025. Most of the reduction occurred in 2022 and 2024, while the 2025 rate was unchanged from 2024. The arithmetic mean over the five years was 16.42 percent, but the mean conceals the direction and irregular timing of change. Annual differences therefore provide a necessary complement to the average.

Table 1

Annual unemployment rate in Georgia

Year	Unemployment rate (%)	Annual change (percentage points)
2021	20.6	Not applicable
2022	17.3	-3.3
2023	16.4	-0.9
2024	13.9	-2.5
2025	13.9	0.0

Source. National Statistics Office of Georgia (2026a). Changes were calculated by the author.

The fitted time trend has a slope of -1.68 percentage points per year and an R-squared value of 0.912. Extrapolation gives a 2026 point estimate of 11.38 percent. Taken alone, these values may appear persuasive. The 95 percent prediction interval, however, extends from 6.99 to 15.77 percent. The interval is wide because the sample is very small and the annual changes vary markedly.

This result exposes two limitations of a simple calculation. First, an average decline of approximately 1.7 percentage points does not justify a narrow forecast range. Second, annual observations cannot support a claim that unemployment predictably falls every summer. Testing seasonality requires quarterly or monthly data and an explicit seasonal model.

Table 2

Diagnostic linear trend for the unemployment rate

Statistic	Result	Interpretation
Observations	5	Too few for a robust structural forecast
Slope	-1.68 pp per year	Average fitted annual decline
R-squared	0.912	In-sample fit, not proof of forecast accuracy
2026 point estimate	11.38%	Conditional extrapolation

Statistic	Result	Interpretation
95% prediction interval	6.99%-15.77%	Uncertainty for a new annual observation

Note. Author's calculations based on National Statistics Office of Georgia (2026a). The model is a diagnostic benchmark and not an official forecast.

The population case produces the third result: a figure must be identified by both reference date and data vintage. The April 2025 release and the current database attach materially different estimates to 1 January 2025. The difference is too large to interpret as ordinary year-to-year demographic change and reflects the later incorporation of census information into the official series.

The current database also reports 3,941.1 thousand residents as of 1 January 2026. Comparing that figure directly with the unrevised 3,704.5 thousand release would falsely imply growth of more than six percent. A valid comparison must use observations from the same statistical vintage or include a documented bridge explaining the revision.

Table 3
Population estimates and data vintage

Source vintage	Reference date	Population (thousand)	Analytical status
Release of 25 April 2025	1 January 2025	3,704.5	Earlier estimate
Database accessed 14 September 2026	1 January 2025	3,930.4	Revised series
Database accessed 14 September 2026	1 January 2026	3,941.1	Current estimate

Sources. National Statistics Office of Georgia (2025, 2026b). Values should not be compared across vintages without revision documentation.

The demographic evidence also contradicts an overly simple narrative. Live births declined from 39,483 in 2024 to 37,867 in 2025, a reduction of approximately 4.1 percent, while the current population estimate increased between 2025 and 2026 (National Statistics Office of Georgia, 2026b). Population change depends on births, deaths, migration, coverage, and revisions. A fertility or migration explanation cannot be inferred from the total population alone.

The fourth result concerns dissemination. Interactive portals expand access and permit rapid comparison of sectoral indicators, but user control does not remove the need for metadata. A chart or scenario generated through the Economic Analysis Portal remains conditional on the selected sector, price basis, period, and assumptions. The portal is most valuable when it helps users reproduce a comparison and inspect the components behind aggregate change.

Together, the cases show that statistical analysis contributes to decision-making in three distinct ways. It describes the observed state, tests relationships or decompositions, and constructs conditional forecasts. These functions should be reported separately. Descriptive improvement does not identify cause; explanatory association does not guarantee predictive accuracy; and a forecast does not become a target merely because it is numerical.

Discussion

The findings confirm the practical importance of statistical methods while narrowing several broad claims commonly made about them. Statistics can improve economic judgment, but it does not automatically produce objectivity. Objectivity depends on transparent definitions, appropriate sampling, reproducible transformation, model diagnostics, and the possibility of independent verification. A method becomes persuasive through its evidential chain, not through mathematical appearance alone.

The unemployment example illustrates the difference between fit and forecast reliability. The trend explains a high share of variation within five observations, yet the prediction interval remains wide. This is not a contradiction. R-squared measures in-sample fit around a particular line; it does not measure the probability that structural conditions will continue. Forecasting texts therefore recommend simple benchmarks, rolling evaluation, and interval forecasts rather than reliance on a single goodness-of-fit statistic (Chatfield, 2000; Hyndman & Athanasopoulos, 2021).

The example also shows why model complexity should be proportionate to available data. With five annual observations, adding multiple explanatory variables would consume degrees of freedom and encourage overfitting. Machine-learning methods would not repair the lack of observations. Evidence from forecasting research shows that flexible methods require careful validation and do not dominate in every setting (Makridakis et al., 2018). A transparent baseline is preferable when the data cannot support a more complex model.

For policy use, the most defensible interpretation is conditional: if the 2021-2025 linear tendency continued unchanged, the point estimate would be 11.38 percent, but plausible variation around that estimate is large. The unchanged rate in 2025 already warns against treating the earlier decline as mechanically persistent. Updated quarterly data, labour-force participation, employment levels, sectoral composition, and uncertainty about future shocks should inform any operational forecast.

The population example is more fundamental because it concerns the measurement base. Census benchmarking can change population denominators used in employment, fertility, income, and per-capita indicators. A revision can therefore alter several economic ratios even when their numerators are unchanged. Analysts should preserve the retrieval date, archive the data vintage, and rerun calculations when a benchmark revision occurs. This practice supports the comparability and transparency principles emphasized in official statistics standards (Eurostat, 2017; United Nations, 2014).

The earlier population estimate should not be described as fraudulent or useless. It was the official estimate available under the information set and methodology of its release date. The methodological error would be to combine it silently with a later revised series. Statistical literacy includes understanding that official values can be provisional and that revision is often evidence of improved measurement rather than institutional failure.

The findings also clarify the role of correlation and regression. Regression can quantify conditional associations and generate predictions under stated assumptions. It does not, by itself, prove that inflation reduces purchasing power through a single channel, that investment causes growth, or that demographic change produces an unattractive business environment. Causal interpretation requires a research design that addresses simultaneity, omitted variables, measurement error, and selection (Wooldridge, 2020).

For firms, the practical implication is to combine macroeconomic indicators with sector-specific evidence. Population totals may inform market size, but purchasing power, regional distribution, age structure, migration, productivity, and digital access may matter more for a particular product. The World Development Report 2021 emphasizes that data create value when governance, infrastructure, and institutional safeguards allow them to be used responsibly (World Bank, 2021).

For public institutions, transparent communication is equally important. Each forecast should state the reference period, source, model, assumptions, update schedule, and uncertainty range. Scenario language should distinguish a baseline from an optimistic or adverse case. When a series is revised, publication systems should preserve revision notes and explain whether historical comparisons remain valid.

The Economic Analysis Portal is useful within this framework because it can shorten the path from data to comparison. Its strongest contribution is not automatic prediction but accessible decomposition and visualization. The analytical responsibility remains with the user: selecting a valid comparison, checking definitions, and avoiding claims that exceed the evidence (National Statistics Office of Georgia, n.d.).

Limitations

This study is an illustrative case analysis, not a comprehensive forecast of Georgia's economy. The unemployment model uses only five annual observations and omits explanatory variables, structural breaks, and quarterly dynamics. Its numerical forecast is included to demonstrate uncertainty and should not be treated as an official projection.

The population comparison identifies a revision but does not reconstruct the full census-benchmarking procedure. The analysis relies on publicly available English-language materials and does not evaluate the internal production systems of Geostat. The portal discussion is documentary; no user testing was conducted.

Future Research

Future research should build a longer quarterly unemployment series and compare naïve, seasonal, autoregressive, and explanatory models through rolling-origin evaluation. Forecast accuracy should be reported out of sample using several measures, while policy interpretation should consider labour-force participation and employment counts alongside the unemployment rate.

A second line of research should quantify how the 2024 census revision changed population denominators and downstream indicators. A reproducible revision matrix could compare vintages by year, region, age, and sex. Research on the Economic Analysis Portal should also test whether metadata prompts and uncertainty displays improve users' interpretation of charts and scenarios.

Conclusion

Statistical analysis is indispensable for assessing and forecasting economic processes, but its credibility depends on disciplined use. The Georgia case shows that averages, annual changes, fitted trends, prediction intervals, and revision metadata answer different questions and must be reported together.

The unemployment rate fell from 20.6 percent in 2021 to 13.9 percent in 2025, but the path was uneven and a five-observation trend produces substantial forecast uncertainty. The population case

demonstrates that revisions can invalidate apparently straightforward comparisons. Analysts must therefore preserve data vintage, verify comparability, state assumptions, and distinguish diagnostic estimates from operational forecasts.

The practical standard is simple: define the indicator, document the source, reproduce the calculation, test the model, report uncertainty, and update the conclusion when the data change. This sequence allows statistical methods to support economic decisions without overstating what the evidence can establish.

Declarations

Ethics approval: Not applicable. The study used publicly available aggregate data and did not involve human participants or personal data.

Conflict of interest: The author declares no conflict of interest.

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