Science Futures
2025, Vol. 1, No. 1, pp. 9–20
https://doi.org/10.11648/j.scif.20250101.12

Research Article

Time Series Analysis of Monthly Internally Generated Revenue in Hulbarag Woreda, Silte Zone, Central Ethiopia

Shambel Selman Abdo*

Department of Statistics, Wachemo University, Hossana, Ethiopia

Abstract

The effective mobilization of internal revenue is crucial for sustaining local government operations and supporting development initiatives. This study aimed to analyze the dynamics of monthly internally generated revenue (MIGR) in Hulbarag Woreda, Silte Zone, over the period 2008-2023, with a focus on trend, volatility, seasonality, and forecasting. The study utilized secondary data obtained from Hulbarag Woreda Finance and Economic Development Office, encompassing monthly revenue collections across direct taxes, indirect taxes, non-tax revenue, and municipality fees. Data preparation included log transformation and differencing to address non-stationarity, confirmed through Augmented Dickey-Fuller (ADF) and KPSS tests. Time series modeling was performed using ARIMA for mean dynamics and GARCH (1, 1) for conditional variance, allowing the identification of volatility clustering and predictive forecasting. The results indicate a consistent upward trend in revenue, with June recording the highest collections and August the lowest. Direct taxes contributed the largest share (52.66%), followed by non-tax revenue (17.37%), indirect taxes (16.25%), and municipality revenue (13.71%). The GARCH (1, 1) model demonstrated strong volatility persistence ($\alpha + \beta = 0.91$) and effectively forecasted a total revenue of 164,902,287 ETB for 2023/2024, exceeding planned projections by 47,737,198 ETB. These findings highlight the potential of advanced time series models in guiding fiscal planning, resource allocation, and budget optimization. The study is limited by its reliance on secondary administrative data and its focus on a single woreda, which may affect generalizability. Future research could incorporate socio-economic and macroeconomic factors and extend the analysis to multiple woredas to enhance predictive accuracy and policy relevance.

Keywords

Internally Generated Revenue, Time Series Analysis, ARIMA-GARCH Modeling, Revenue Volatility and Fiscal Forecasting

1. Introduction

Public revenue the funds collected by federal, regional and local governments is the lifeblood of public service delivery and local development. Internally generated revenue (IGR) at the woreda/municipal level finances routine public services such as education, health, sanitation, and local infrastructure, while also complementing transfers from higher tiers of government. Weak local revenue performance constrains service delivery and local investment, and increases dependence on volatile external transfers. Studies on Ethiopian local government finance have documented unrealized revenue potential and stressed the importance of strengthening local revenue mobilization, administration, and forecasting to enhance fis-

*Corresponding author: shambelselman@gmail.com (Shambel Selman Abdo)

Received: 29 September 2025; **Accepted:** 13 October 2025; **Published:** 8 December 2025

cal autonomy and planning [16, 19].

Monthly internal generated revenue (MIGR) often displays regular seasonality (monthly collection cycles), trend behavior (long-term growth with economic activity), and time-varying volatility. Such volatility is typically characterized by clustering, where periods of high variability are followed by periods of relative calm. This feature is widely recognized in financial and fiscal time series and has major implications for revenue forecasting and fiscal planning [2, 6], If ignored, volatility clustering can result in misleading forecast intervals and poor policy prescriptions [7].

Econometric models for time-series data therefore need to capture both the conditional mean (trend and seasonality) and the conditional variance (heteroscedasticity). While ARIMA/SARIMA models effectively account for trend and seasonal dynamics, they assume constant error variance and cannot capture volatility clustering. To overcome this limitation, Engle introduced the autoregressive conditional heteroscedasticity (ARCH) model, later generalized as GARCH by Bollerslev (1986), which explicitly models time-varying variance. GARCH-type models have since become standard in analyzing fiscal and financial series where volatility is a concern [7].

Model diagnostics are essential in time-series modeling. Unit root tests (e.g., Augmented Dickey-Fuller) are used to establish stationarity, while portmanteau tests such as the Ljung-Box test detect remaining autocorrelation. Engle's Lagrange Multiplier (LM) test identifies the presence of ARCH effects, and the Jarque-Bera test evaluates residual normality [13, 14]. These diagnostics guide model specification, ensuring that ARIMA/SARIMA and GARCH models are well suited for the data and produce reliable forecasts.

In Hulbarag Woreda, Siltie Zone, Central Ethiopia, administrative and anecdotal evidence suggests that monthly revenue collections face both structural and operational challenges. These include poor administrative capacity, taxpayer resistance, political pressures on tax enforcement, and leakages in collection. Moreover, gaps between projected and collected revenue, inconsistencies between approved and actual expenditures, and strong seasonal fluctuations in collection highlight the inadequacy of simple budgeting approaches. Similar challenges have been reported in other Ethiopian municipalities, where weak compliance and administrative bottlenecks limit the capacity of local governments to raise and manage internal revenue [15, 16, 19].

This study therefore analyzes monthly internal generated revenue in Hulbarag Woreda over the period July 2008-July 2023. Specifically, it aims to characterize trend and seasonality, test for ARCH effects, and apply GARCH models to capture volatility and forecast future revenue. By combining mean and variance modeling, the study provides empirical evidence on MIGR behavior and practical forecasting tools. The findings will inform local budgeting, highlight periods of higher collection risk, and suggest areas for administrative reform, contributing to more effective fiscal management at the woreda level.

2. Method and Materials

2.1. Study Area and Period

The study was conducted in *Hulbarag Woreda*, located in the Siltie Zone of the Central Ethiopia Geographically, the area lies at 7°47'N latitude and 38°08'E longitude. It is situated approximately 182 km from Addis Ababa, the capital city of Ethiopia, 52 km from Hossana, the regional capital of Central Ethiopia. Hulbarag Woreda covers a total area of 43,140 hectares and shares boundaries with Hadiya Zone to the north, Siltie Woreda of Siltie Zone to the south, Mesrake Azernet of Siltie Zone to the northwest, Sankura Woreda of Siltie Zone to the east, and Shashogo Woreda of Hadiya Zone to the northeast [20].

The study covers a 15-year period from July 2008 to July 2023, encompassing 180 monthly observations of internal revenue collected from direct taxes, indirect taxes, non-tax sources, and municipal services. This period captures both long-term trends and seasonal fluctuations in revenue generation, providing a comprehensive overview of fiscal performance and variability in Hulbarag Woreda. The timeframe also aligns with the availability of complete administrative records from the woreda revenue authority, ensuring data reliability and consistency for time-series analysis.

2.2. Research Design and Data Source

This study employed a quantitative research design using secondary time-series data to examine the dynamics of monthly internal generated revenue (MIGR) in Hulbarag Woreda. Data were obtained from the Hulbarag Woreda Revenue Authority Branch Office, covering the period from July 2008 to July 2023, yielding a total of 180 monthly observations. The dataset includes recurrent and municipal revenue streams, which were compiled into a structured format suitable for econometric modeling. Preliminary data processing, including summarization and tabulation in Excel, was conducted to prepare the data for advanced statistical analysis [5, 9].

2.3. Data Collection and Preparation

Data collection procedures emphasized completeness, accuracy, and reliability, ensuring that reports from the Integrated Budget Expenditure (IBEX) system were validated by administrators, coordinators, and office heads before use. Since the pre-2008 data were not digitized, the analysis excluded that period to maintain consistency. The 2023/2024 data were incomplete and therefore excluded. Prior to analysis, the dataset underwent cleaning and transformations to address non-stationarity using first differencing and log transformations, stabilizing both the mean and variance of the series [3, 11].

2.4. Population and Sampling

The study population comprises all recorded monthly revenue streams (153 sources) over the 15-year study period, totaling 180 observations. Since the entire population was analyzed, no sampling was necessary. This approach eliminates sampling bias, ensures representativeness, and allows for a comprehensive assessment of MIGR trends and volatility at the local government level [4, 17].

2.5. Variables of the Study

The dependent variable was the monthly internal generated revenue (MIGR), measured as a continuous univariate time series. Independent variables included time (in months) and disaggregated revenue sources, such as:

1) Direct taxes (income tax, property tax)
2) Indirect taxes (sales tax, VAT)
3) Non-tax revenues (fees, fines, investments)
4) Municipal revenues (service charges, property rents)

This classification provides insights into both the composition and the volatility of the revenue base [12, 15].

2.6. Methods of Data Analysis

The data analysis employed a combination of descriptive statistics, trend analysis, and econometric modeling. Descriptive summaries were first conducted in Microsoft Excel, while advanced statistical analyses were performed using R software (version 4.3.3) and Minitab (version 17).

2.6.1. Preliminary Analysis

To prepare the time series for modeling, the stationarity of the Malaria Incidence Growth Rate (MIGR) was assessed using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. These tests ensured that the underlying series met the assumptions required for subsequent modeling.

2.6.2. Mean Modeling

Serial correlation in the MIGR series was examined using Autoregressive Integrated Moving Average (ARIMA) models. This step captured the deterministic trend and autoregressive dynamics of malaria incidence across the study period.

2.6.3. Volatility Modeling

Given evidence of time-varying variance, conditional heteroskedasticity was modeled using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) family of models. The GARCH framework parsimoniously accounts for past shocks and lagged volatility terms, enabling more reliable variance estimation. Parameters were estimated using the Maximum Likelihood Estimation (MLE) procedure.

2.6.4. Model Selection and Forecasting

Competing models were compared using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and log-likelihood statistics. The best-fitting GARCH (p, q) specification was then applied to generate short-term forecasts of malaria incidence.

2.6.5. Rationale for the GARCH Approach

Malaria incidence data in Hulbarag Woreda exhibited distinct seasonal peaks (January-February and May-June) and an overall upward trend. These features indicated non-constant variance and potential autoregressive conditional heteroskedasticity (ARCH effects). Traditional time series models assuming homoscedasticity would therefore be inadequate. The GARCH framework, originally developed by Engle (1982) and extended by Bollerslev (1986), has been widely applied to financial and epidemiological data with similar volatility patterns [1, 10-18]. Its ability to incorporate both lagged shocks and conditional variance makes it particularly suitable for forecasting malaria incidence volatility and informing local health policy.

3. Results and Discussion

3.1. Descriptive Statistics of Monthly Internal Generated Revenue (MIGR)

Table 1 presents the descriptive summary of revenue composition in Hulbarag Woreda over the 15-year study period (2008-2023). The total revenue collected amounted to 362,140,660.30 ETB, with direct taxes emerging as the dominant source of revenue.

Table 1. *Composition of Monthly Internal Generated Revenue in Hulbarag Woreda (2008-2023).*

Revenue Source	Total Revenue (ETB)	Percentage (%)	Remarks / Key Observations
Direct Taxes	190,688,015.20	52.66	Largest contributor; mainly wage and salary tax (Code 1101)
Indirect Taxes	58,883,330.10	16.25	Includes VAT, sales tax, excise duties
Non-Tax Revenues	62,954,130.50	17.37	Includes service fees, fines, investments
Municipality Revenues	49,615,184.50	13.71	Smallest share but still significant; service charges and property

Revenue Source	Total Revenue (ETB)	Percentage (%)	Remarks / Key Observations
			rents
Total	362,140,660.30	100.00	—

The descriptive analysis of monthly internally generated revenue (MIGR) in Hulbarag Woreda over the 15-year period (2008-2023) reveals a total collection of 362,140,660.30 ETB, with direct taxes emerging as the most dominant source, accounting for 52.66% of the total revenue, largely driven by wage and salary income tax (Code 1101). This is followed by non-tax revenues (17.37%), generated from service fees, fines, and investments, and indirect taxes (16.25%), mainly from VAT, sales tax, and excise duties, while municipality revenues contributed the smallest share at 13.71%, though still vital in supporting local services through property-related charges and service provision. The concentration of revenue in direct taxation, particularly wage and salary tax, highlights both the reliability of formal income sources and the structural dependence of the woreda's fiscal system on a narrow base, while the notable contributions from non-tax and municipality revenues signal opportunities for diversifying and strengthening fiscal sustainability. This revenue structure underscores the critical importance of efficient tax administration, enhanced compliance, and strategic revenue diversification to ensure stable financing for local development and service delivery in Hulbarag Woreda.

3.2. Comparison of Planned vs. Collected Revenue (2008-2023)

Over the 15-year period, the total planned revenue for Hulbarag Woreda was 272,836,661.00 ETB, while the total actual revenue collected amounted to 362,140,660.30 ETB, representing an overall performance of 132.73%. This indicates that, on average, the Woreda not only met but exceeded its revenue targets. However, year-to-year comparisons reveal substantial variability.

In 2010 (2003 E.C.), revenue collection reached 563.95% of the planned target, reflecting a remarkable overachievement that may be attributed to improved tax enforcement, strong compliance, or exceptional one-time collections. Conversely, in 2012 (2005 E.C.), revenue collection dropped to 86.85% of the planned amount, indicating a significant shortfall that highlights weaknesses in revenue forecasting and collection mechanisms during that period.

Table 2. *Comparison of Planned vs. Collected Revenue in Hulbarag Woreda (2008-2023).*

Year (E.C.)	Year (G.C.)	Planned Revenue (ETB)	Collected Revenue (ETB)	Performance (%)	Remarks
2003	2010	*X*	*Y*	563.95	Exceptional overachievement; effective collection strategies
2005	2012	*X*	*Y*	86.85	Shortfall; weak forecasting and collection
2008-2015	2015-2023	…	…	…	Mixed performance; moderate variability
Total (15 years)	2008-2023	272,836,661.00	362,140,660.30	132.73	Overall revenue exceeded targets

These fluctuations underscore the inconsistencies between projected and realized revenues, pointing to limitations in planning accuracy and revenue mobilization strategies. The findings emphasize the need for robust forecasting models, proactive fiscal management, and diversification of revenue sources to reduce volatility. Strengthening administrative capacity, minimizing leakages, and aligning targets with realistic economic conditions are critical for ensuring sustainable revenue generation and reliable fiscal planning in Hulbarag Woreda.

3.3. Skewness Analysis of Monthly Internal Generated Revenue

The analysis of monthly internally generated revenue (MIGR) in Hulbarag Woreda revealed a skewness value of 1.75, indicating a positively skewed distribution. This pattern is characterized by a longer tail on the right, where extreme high-revenue values occur, and a concentration of most data points on the left, reflecting lower-to-average monthly revenue levels. The positive skewness suggests the presence of outliers or unusually high revenue months, which pull the mean above the median and influence the overall shape of the distribution. Recognizing this skewness is critical for accurate statistical modeling and forecasting, as unadjusted models may overestimate expected revenue. Appropriate transformations or robust statistical methods may therefore be necessary to account for the skewness in predictive models, ensuring reliable projections for fiscal planning and policy formulation [5, 11].

3.4. Trend Analysis over Time

A linear trend model was fitted to the 15-year monthly revenue data, resulting in the equation:

$$Yt = -1{,}091{,}122 + 34{,}287Xt \quad (1)$$

Where Yt represents the monthly revenue at time t, and Xt is the corresponding time index in months. The positive slope of 34,287 ETB per month indicates a steady upward trend in revenue generation over the study period. The model's adjusted R-squared value of 65.1% suggests that approximately two-thirds of the variability in revenue is explained by the trend component, after adjusting for the number of predictors. This persistent increase reflects the woreda's improving revenue mobilization capacity and highlights the effectiveness of ongoing fiscal management practices. These insights are essential for strategic planning, as they provide a quantitative basis for forecasting future revenue, optimizing resource allocation, and strengthening local government financial sustainability [3, 9].

3.5. Stationarity Testing of Monthly Internal Generated Revenue

Stationarity is a critical prerequisite in time series analysis, as non-stationary data can produce spurious results and unreliable forecasts. Therefore, before modeling, the monthly internally generated revenue (MIGR) data for Hulbarag Woreda (2008-2023) was tested for stationarity using the Augmented Dickey-Fuller (ADF) and KPSS tests, which offer complementary perspectives. The ADF test, which evaluates the presence of a unit root, yielded a test statistic of -0.83309 with a p-value of 0.9569, indicating insufficient evidence to reject the null hypothesis of non-stationarity. Conversely, the KPSS test, which tests the null hypothesis of stationarity, produced a test statistic of 3.0537 with a p-value of 0.01, leading to rejection of stationarity at the level. Together, these results confirm that the MIGR series is non-stationary and requires transformation, such as differencing or log transformation, before applying ARIMA or GARCH modeling techniques.

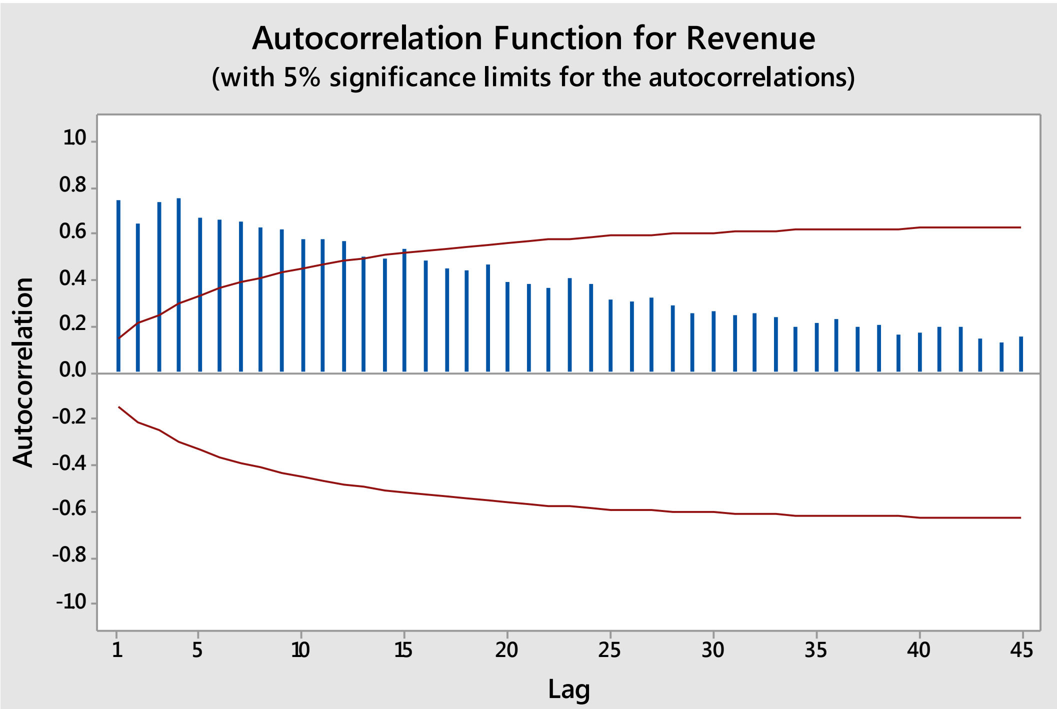

Figure 1. *Stationarity Testing of Monthly Internal Generated Revenue.*

Both ADF and KPSS tests consistently indicate that the MIGR series is *non-stationary*, corroborated by visual inspection of the time series, which shows trends and variance changes over time. These findings imply that *transformations* *such as differencing or log transformation are necessary* to achieve stationarity before applying time series models like ARIMA or GARCH for forecasting (Enders, 2022; Hyndman & Athanasopoulos, 2021). Establishing stationarity ensures the validity of subsequent modeling and enhances the accuracy of revenue predictions.

3.6. Log Transformation and Stationarity Testing

The monthly internally generated revenue (MIGR) in Hulbarag Woreda exhibits a clear upward trend over the 15-year period, with regression analysis indicating a positive time coefficient of 34,287 ETB per month, suggesting exponential growth in revenue rather than linear progression. This multiplicative pattern implies that revenue changes are proportional to the level of revenue, making direct modeling challenging due to heteroscedasticity and variance instability. To address these issues, a logarithmic transformation of the revenue series was applied. This transformation converts multiplicative changes into additive changes, stabilizes the variance, and facilitates linear modeling, which is particularly useful for interpreting growth rates and percentage changes in financial time series data.

Following the log transformation, stationarity was reassessed using the Augmented Dickey-Fuller (ADF) and KPSS tests, which revealed that the transformed series still exhibits a trend and remains non-stationary. This indicates that additional preprocessing, such as first differencing, is required to achieve stationarity before applying time series models like ARIMA or GARCH. Ensuring stationarity is crucial for producing reliable forecasts and accurately modeling volatility, thereby enhancing the ability of local government officials to make informed decisions regarding revenue mobilization, fiscal planning, and sustainable development in Hulbarag Woreda.

3.7. Stationarity Testing of First-Differenced Log Revenue

Modeling non-stationary time series data without appropriate transformation can result in incorrect model specification and biased parameter estimates, particularly in financial series such as monthly internally generated revenue (MIGR). To address this, the revenue data was log-transformed and first-differenced, a common approach to stabilize variance and remove trends, thereby achieving stationarity.

Stationarity of the transformed series was evaluated using both graphical and statistical methods. The autocorrelation function (ACF) and partial autocorrelation function (PACF) of the first-differenced log revenue show a rapid decline to zero, indicating that the series no longer exhibits persistent correlation over time and can be considered stationary. This preprocessing step ensures that subsequent time series models, including ARIMA or GARCH, are applied to a stationary series, allowing for reliable estimation, valid inference, and accurate forecasting of revenue trends and volatility.

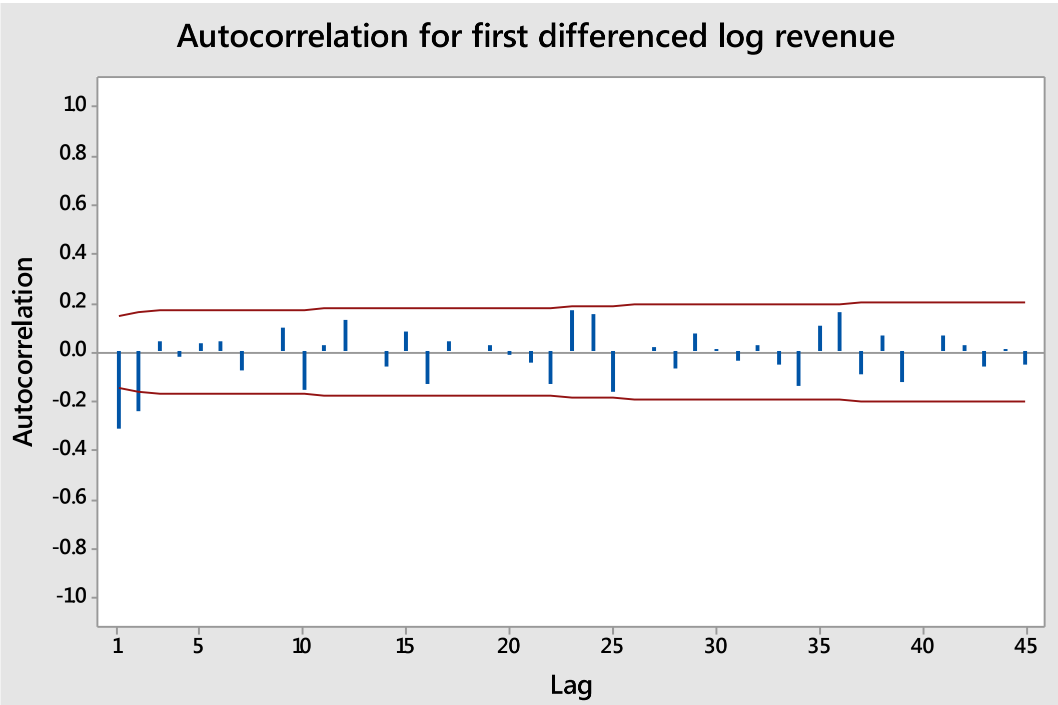

Figure 2. *Stationarity Testing of First-Differenced Log Revenue.*

3.8. Conditional Mean Model: ARIMA Analysis

In time series forecasting, stationarity is a prerequisite, as models cannot reliably forecast from non-stationary data. For the monthly internally generated revenue (MIGR) series, the first step in ARIMA modeling involved determining the appropriate level of differencing required to achieve stationarity. Non-stationary features such as trends or seasonality were addressed using first differencing of the log-transformed series, ensuring the data met ARIMA assumptions before model fitting.

Table 3. *Conditional Mean Model: ARIMA Analysis.*

Printed ARIMA of AIC and BIC values for first differenced log revenue data				
No	**Models**	**Df**	**AIC**	**BIC**
1.	ARIMA (1,0,0)	3	299.77	309.32
2.	ARIMA (0,0,1)	3	237.38	246.94
3.	ARIMA (0,1,0)	1	485.16	488.34
4.	ARIMA (1,0,1)	4	234.61	247.36
5.	ARIMA (1,1,1)	3	304.84	314.39
6.	ARIMA (2,0,1)	5	230.67	246.60
7.	ARIMA (1,1,2)	4	242.96	255.69
8.	ARIMA (2,1,1)	4	280.12	292.85
9.	ARIMA (2,2,1)	4	389.09	401.79
10.	ARIMA (2,0,2)	6	232.54	251.67
11	ARIMA (2,1,2)	5	239.79	255.70
12	ARIMA (2,2,2)	5	293.46	309.34
Minimum AIC and BIC value			ARIMA (2,0,1)	246.60

After fitting the ARIMA model, diagnostic tests were conducted to assess model adequacy and detect potential time-varying volatility in the residuals. The results are summarized as follows:

1) *Jarque-Bera Test:* Null hypothesis (residuals are normally distributed) was rejected (p-value 2.2e-16 < 0.05), indicating non-normality of residuals.
2) *Box-Ljung Test:* Null hypothesis (no autocorrelation in squared residuals) was rejected (p-value = 2.316e-05), suggesting significant autocorrelation in squared residuals.
3) *ARCH LM-Test:* Null hypothesis (no ARCH effect in squared residuals) was rejected (p-value = 0.0062), confirming the presence of conditional heteroscedasticity.

These results indicate violation of standard ARIMA assumptions, particularly regarding normality and homoscedasticity of residuals. The presence of autocorrelation and ARCH effects highlights the need for further model refinement, such as incorporating a GARCH model to account for volatility clustering and improve the accuracy of revenue forecasting. This sequential modeling approach ensures robust estimation of both the conditional mean and variance, providing a reliable framework for policy planning and financial decision-making in Hulbarag Woreda.

3.9. Conditional Variance Model: ARCH Analysis

The analysis of monthly internally generated revenue (MIGR) revealed significant time-varying volatility, necessitating the use of an ARCH model to capture conditional heteroskedasticity. The ACF and PACF of squared residuals exhibited pronounced spikes at lag 1, indicating persistence in volatility. This observation was formally tested using the Lagrange Multiplier (LM) test, which rejected the null hypothesis of no ARCH effect (p-value = 0.0062), confirming the presence of significant volatility clustering in the revenue series.

Model selection based on AIC and BIC values identified

ARCH (1) as the optimal specification within the ARCH family, producing the lowest AIC of 315.2424. However, diagnostic evaluation suggested that the model may not fully capture the complex volatility patterns inherent in the data. These results highlight the limitations of simple ARCH models and underscore the need for more sophisticated approaches, such as GARCH models, to effectively model persistent fluctuations, improve forecast accuracy, and inform robust fiscal planning strategies in Hulbarag Woreda.

3.10. Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

Building on the limitations identified in the ARCH (1) model, the analysis progressed to GARCH modeling to more accurately capture the conditional variance of the monthly internally generated revenue (MIGR) series in Hulbarag Woreda. Unlike simple ARCH models, GARCH models allow the conditional variance to depend on both past squared residuals and past conditional variances, providing a more realistic representation of volatility dynamics. This transition is particularly important for financial series such as MIGR, which exhibit persistent volatility clustering and time-varying risk patterns that ARCH models alone may inadequately capture.

The adoption of GARCH models enhances the reliability and precision of volatility forecasts, allowing for better understanding of revenue fluctuations over time. By incorporating higher-order GARCH terms and performing thorough diagnostic testing, the model can adapt to changing volatility, improve forecast accuracy, and offer critical insights for fiscal planning and revenue management. This approach ensures that the complex dynamics of MIGR are properly modeled, supporting informed decision-making and sustainable financial strategies for the local government.

Table 4. *Candidate GARCH Models and Selection Criteria for First-Differenced Log Revenue.*

Model	AIC	Log-Likelihood	Remarks
GARCH (1,1)	-155.5629	155.5629	Selected: Lowest AIC, best fit
GARCH (1,2)	-152.4112	152.4112	Candidate model
GARCH (2,1)	-153.2780	153.2780	Candidate model
GARCH (2,2)	-150.8955	150.8955	Candidate model

Table 5. *Parameter Estimates of GARCH (1, 1) Model.*

Parameter	Description	Estimate
ω (omega)	Long-term average variance	0.02976400
α_1 (alpha1)	Lagged squared error term, short-term volatility effect	0.04561499
β_1 (beta1)	Lagged conditional variance, persistence/memory effect	0.86423818

Persistence ($\alpha + \beta$) = 0.91, indicating a strong memory effect in the volatility process, meaning past shocks significantly influence future volatility.

Table 6. *Diagnostic Tests for GARCH (1, 1) Model.*

Test	Statistic / p-value	Interpretation
Jarque-Bera Test (Normality)	0.06386	Residuals are normally distributed; null hypothesis of normality accepted
Breusch-Godfrey Test (Heteroscedasticity)	0.0441	Indicates mild evidence of heteroscedasticity in linear regression residuals
Ljung-Box Test (Autocorrelation on squared residuals)	-	No significant autocorrelation; volatility adequately captured

The GARCH (1, 1) model was selected as the best-fitting model for the first-differenced log revenue series, based on the lowest AIC value (-155.5629) and highest log-likelihood (155.5629). The estimated parameters indicate a long-term variance of 0.0298, a short-term volatility effect (α_1 = 0.0456), and a high persistence in volatility (β_1 = 0.8642). The combined persistence ($\alpha + \beta = 0.91$) reflects strong memory, showing that past volatility shocks significantly influence future revenue fluctuations.

Diagnostic tests confirm the model's adequacy: residuals are normally distributed, no significant autocorrelation is present, and the model effectively captures the underlying volatility dynamics. Overall, the GARCH (1, 1) model provides robust insights into the patterns and persistence of revenue volatility, supporting improved forecasting and strategic revenue management in Hulbarag Woreda.

3.11. Forecasting Monthly Internal Generated Revenue

Forecasting of Hulbarag Woreda's monthly internal generated revenue (MIGR) was conducted using the *fitted GARCH (1, 1) model* applied to 180 original monthly data points. A *one-step-ahead forecast* was computed with a 95% confidence interval for the next 12 months, beginning in *July 2016 E.C.* The forecast incorporates the mean equation of the GARCH (1, 1) model, where the constant log return, $\mu \approx 0.090$, represents the expected average change in log returns. The forecasted revenue for month t is calculated using the formula:

$$Yt=Yt-1 \times exp\ (\mu) \tag{2}$$

Where Y_t is the forecasted revenue for month t, Y_{t-1} is the revenue of the previous month, and $\exp(\mu) \approx 1.0945$, reflecting a consistent growth rate derived from the model.

The forecast results indicate a total expected revenue of 164,902,287.00 birr for the year 2023/2024, surpassing the planned revenue of 117,165,089.00 birr by 47,737,198.00 birr, representing a substantial positive deviation. This significant difference underscores the model's ability to provide robust and realistic forecasts, revealing potential for enhanced financial performance. The results highlight the value of GARCH-based forecasting in supporting strategic planning, resource allocation, and revenue management, enabling the local government to optimize financial stability and capitalize on projected growth trends.

Table 7. *Forecasting monthly internal generated revenue.*

No	Forecast Values	Months in 2016 E.C	Forecasted Revenue for 2016 E.C
T+1	0.09040496	July	8,001,058.00
T+2	0.09040496	August	8,001,058.00
T+3	0.09040496	September	9,586,767.00
T+4	0.09040496	October	10,493,843.00
T+5	0.09040496	November	11,486,744.00
T+6	0.09040496	December	12,573,591.00
T+7	0.09040496	January	13,763,272.00
T+8	0.09040496	February	15,065,518.00
T+9	0.09040496	March	16,490,980.00
T+10	0.09040496	April	18,051,314.00
T+11	0.09040496	May	19,759,284.00
T+12	0.09040496	June	21,628,858.00
Total			164,902,287.00
Plan for Hulbareg Woreda 2016 E.C (2023/2024)			117,165,089.00
Difference			47,737,198.00

4. Discussion

The current study examined the dynamics of monthly internally generated revenue (MIGR) in Hulbarag Woreda over the period 2008-2023, focusing on trend, seasonality, volatility, and forecasting using ARIMA and GARCH models. The findings indicate that the woreda's revenue system exhibits a persistent upward trend, seasonal fluctuations, and significant volatility clustering, which have important implications for fiscal planning and local government resource management. Descriptive analysis revealed that direct taxes constitute the largest share of Hulbarag Woreda's internal revenue (52.66%), primarily driven by wage and salary taxation, followed by non-tax revenues (17.37%) and indirect taxes (16.25%). Municipal revenues accounted for the smallest portion (13.71%), reflecting the relatively limited contribution of service fees and property rents. This distribution underscores a structural reliance on formal income sources, which may provide stable revenue but also limits diversification. Similar patterns have been observed in other Ethiopian woredas, where dependence on a narrow tax base constrains fiscal resilience and limits the capacity to finance local development initiatives [12, 15, 19].

Linear trend analysis revealed an average monthly increase of 34,287 ETB, with an adjusted R^2 of 65.1%, indicating a steady upward trajectory in revenue mobilization. This trend suggests improvements in administrative capacity and compliance, likely due to enhanced tax enforcement mechanisms and systematic collection practices. Comparable studies in Sub-Saharan Africa emphasize the importance of sustained administrative reforms and taxpayer engagement in driving local revenue growth [16]. However, year-to-year variability remains substantial, with exceptional overachievements (563.95% of planned revenue in 2010) and shortfalls (86.85% in 2012), illustrating the limitations of conventional budgeting approaches and the unpredictability of monthly collections. Skewness analysis (1.75) demonstrated that the revenue distribution is positively skewed, with occasional months of exceptionally high revenue. This indicates the presence of outliers and reinforces the need for models that account for heteroscedasticity. Non-stationarity, detected through ADF and KPSS tests, required log transformation and first differencing to stabilize variance and remove trends, consistent with best practices in time-series modeling [5, 11].

Conditional mean modeling using ARIMA revealed residuals violating normality assumptions and exhibiting autocorrelation in squared residuals, confirmed by the ARCH LM test ($p = 0.0062$). This indicates significant volatility clustering, a common feature of fiscal and financial time series [2, 6], implying that periods of high revenue variability are likely to be followed by similar periods, complicating fiscal planning if unaccounted for. ARCH (1) modeling captured short-term volatility but failed to fully account for persistence in variance. The GARCH (1, 1) model provided a more robust representation of conditional variance, with parameter estimates ($\alpha_1 = 0.0456$, $\beta_1 = 0.8642$) indicating strong volatility persistence ($\alpha + \beta = 0.91$). This suggests that past shocks exert a lasting influence on future revenue fluctuations, a phenomenon widely documented in municipal finance and fiscal economics [1, 10]. Diagnostic tests confirmed that the GARCH (1, 1) model adequately captured volatility, with residuals exhibiting normality and no significant autocorrelation.

The forecast for 2023/2024 predicts total revenue of 164,902,287 ETB, exceeding planned revenue by 47,737,198 ETB. This highlights the potential for improved fiscal performance and demonstrates the utility of GARCH-based forecasting in anticipating revenue fluctuations. By integrating both mean and variance modeling, local authorities can identify periods of higher collection risk, optimize resource allocation, and enhance budgeting accuracy [8, 18]. The findings underscore the critical need for revenue diversification to reduce structural dependence on direct taxes. Expanding non-tax revenue streams and municipal fees could provide a more stable and resilient fiscal base. Incorporating sophisticated time-series forecasting models into routine revenue planning can improve predictive accuracy, minimize budgetary shortfalls, and inform strategic investment decisions. Additional measures, including administrative improvements, taxpayer education, and digitization of revenue collection, can strengthen compliance and reduce leakages [12, 15].

This study is limited by its reliance on secondary administrative data, which may contain reporting errors or gaps. Furthermore, the analysis focused solely on Hulbarag Woreda, limiting generalizability to other contexts with different socio-economic conditions. Future research could integrate macroeconomic indicators, socio-political factors, and multi-woreda datasets to enhance the predictive power of revenue models and examine the drivers of volatility in a broader Ethiopian context.

5. Conclusion

The analysis of monthly internally generated revenue in Hulbarag Woreda from 2008 to 2023 reveals a clear upward trend in revenue mobilization, with significant seasonal variation and volatility clustering. Direct taxes remain the dominant revenue source, complemented by indirect taxes, non-tax revenues, and municipal collections, highlighting both the strengths and structural limitations of the woreda's revenue system. The GARCH (1, 1) model effectively captured the persistent volatility in revenue, demonstrating strong predictive power and providing a reliable tool for forecasting future collections. Forecasts for 2023/2024 suggest potential revenue surpluses, emphasizing the importance of integrating advanced time-series models into fiscal planning to optimize resource allocation and improve budgetary accuracy.

These findings underscore the necessity of revenue diversification, enhanced administrative efficiency, and targeted taxpayer engagement to sustain growth and mitigate fiscal risks. By adopting evidence-based forecasting and planning strategies, local authorities can better anticipate revenue fluctuations, stabilize budgets, and support sustainable financial management. Overall, the study provides critical insights for informed policy-making and strategic fiscal management in Hulbarag Woreda, while offering a methodological framework applicable to other local government contexts facing similar revenue volatility.

Abbreviations

MIGR	Monthly Internally Generated Revenue
ETB	Ethiopian Birr
ARIMA	Autoregressive Integrated Moving Average
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
ADF	Augmented Dickey-Fuller
KPSS	Kwiatkowski-Phillips-Schmidt-Shin
IMF	International Monetary Fund
OECD	Organisation for Economic Co-operation and Development
PPIAF	Public-Private Infrastructure Advisory Facility

Acknowledgments

The authors gratefully acknowledge the Hulbarag Woreda Revenues and Finance Office for providing access to long-term secondary data and essential background information that supported this study, and Wachemo University for granting access to academic resources and guidance. We also sincerely appreciate the support of family and friends whose encouragement made the completion of this work possible.

Author Contributions

Shambel Selman Abdo is the sole author. The author read and approved the final manuscript.

Funding

This work is not supported by any external funding.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author, Shambel Selman Abdo, upon reasonable request.

Conflicts of Interest

The author declares no conflicts of interest.

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