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MODELLING TUBERCULOSIS CASE DETECTION RATES IN UGANDA

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ABSTRACT

This study models tuberculosis (TB) case detection rates in Uganda using historical data from 2000 to 2022 and applies autoregressive integrated moving average (ARIMA) approach for time-series analysis. Data sourced from the World Bank is utilized, with TB case detection rate (%, all forms) as the dependent variable, while autoregressive (AR) and moving average (MA) components serve as independent variables. Parameter estimation, performed using conditional least squares (CLS), reveals a negative and statistically significant MA(1) coefficient (-0.896946), suggesting that approximately 90% of the current TB case detection rate is influenced by shocks or errors from the previous period. The estimated ARIMA (1, 2, 1) model is covariance stationary and invertible, confirming its robustness for forecasting trends in TB case detection rates. Projections from 2023 to 2032 suggest a gradual improvement, with the forecast indicating a steady upward trend from 92.3% in 2023 to 95.1% by 2032, although it falls short of 100% detection rate target. We recommend strengthening surveillance systems, enhancing policy interventions, and ensuring continuous investment in TB detection efforts to sustain this positive trajectory.

KEY WORDS: *ARIMA modelling, Tuberculosis case detection rate*

INTRODUCTION

Tuberculosis (TB) remains a critical public health concern globally, with significant implications for health systems, economic productivity, and social well-being. Despite concerted efforts to combat the epidemic, TB continues to be one of the leading causes of morbidity and mortality, particularly in low- and middle-income countries (WHO 2021). Uganda has faced persistent challenges in achieving high TB case detection rates, which are fundamental for effective diagnosis, treatment, and prevention strategies. According to data from the World Bank (2023), Uganda's TB case detection rates between 2000 and 2022 have consistently fallen below 100%, highlighting potential risks of under-diagnosis and further escalation of the epidemic.

Effective modelling and forecasting of TB case detection rates are essential for understanding historical trends and predicting future trajectories. Such analysis provides critical insights for policymakers to strengthen health interventions and allocate resources effectively (Houben & Dodd 2016). Time-series modelling techniques, particularly the autoregressive integrated moving average (ARIMA) approach, are well-suited for capturing temporal dependencies and forecasting trends based on historical data (Box & Jenkins 1976). ARIMA models have proven effective in epidemiological studies for analyzing and predicting disease trends, offering robust and reliable results (Shumway & Stoffer 2000).

This study employs ARIMA modelling, combined with conditional least squares (CLS) estimation, to analyze TB case detection rates in Uganda. The CLS method is particularly advantageous for parameter estimation in time-series models, as it minimizes the sum of squared residuals, ensuring accurate parameter estimates for autoregressive (AR) and moving average (MA) components (Gujarati & Porter 2009). This combined methodological approach enhances the model's precision and reliability, making it a valuable tool for forecasting and policy formulation.

The rationale for this study stems from the urgent need to improve TB case detection rates in Uganda to reduce the disease burden and prevent further escalation of the epidemic. By modelling detection rates and forecasting future trends, this research aims to inform evidence-based decision-making, enhance surveillance systems, and support the design of targeted interventions. The findings are expected to guide policymakers in prioritizing resources, optimizing detection strategies, and ultimately strengthening Uganda's capacity to control TB.

LITERATURE REVIEW

Tuberculosis (TB) remains one of the most significant infectious diseases globally, posing severe public health challenges. According to the World Health Organization (WHO 2022), an estimated 10.6 million people fell ill with TB in 2021, with 1.6 million deaths recorded. TB case detection rates vary widely across countries, influenced by differences in healthcare infrastructure, diagnostic technologies, and surveillance systems (Lönnroth et al. 2009). Studies have emphasized the need for accurate and timely detection rates to mitigate the spread and improve treatment outcomes (Dye et al. 2005). Time-series models, such as ARIMA, have been applied in various countries to analyze trends and forecast detection rates, demonstrating their utility in epidemiological research (Siamba et al. 2023).

In Sub-Saharan Africa, TB prevalence remains disproportionately high, exacerbated by weak health systems, poverty, and high HIV co-infection rates (Lawn & Zumla 2011). Case detection rates in the region are often below global targets due to inadequate diagnostic tools and underreporting (World Bank 2023). Empirical studies in Kenya and Nigeria highlight the application of ARIMA models to predict TB trends and inform public health interventions (Olanrewaju et al. 2020). These studies underscore the importance of robust statistical models for improving surveillance and resource allocation in low-resource settings.

Uganda has made progress in TB control, however data from the World Bank (2023) indicate annual detection rates consistently below 100% between 2000 and 2022. This shortfall highlights persistent gaps in TB surveillance and case identification systems. Research by Kirenga et al. (2015) revealed that delayed diagnosis and limited access to healthcare facilities contribute to low detection rates. Despite policy efforts, Uganda faces challenges related to data quality and forecasting capabilities, necessitating evidence-based approaches like ARIMA modelling for effective planning and evaluation (Nyoni & Nyoni 2020). Nevertheless, there is limited research on TB case detection rates in Uganda. Previous research primarily focused on prevalence and treatment success rates rather than predictive modelling. This study addresses this gap by offering a data-driven framework for forecasting detection rates, contributing to improved policy formulation and resource allocation.

This study is grounded in the Theory of Epidemiological Transition, which explains shifts in disease patterns due to socioeconomic development (Omran 2005). TB remains a major burden in countries undergoing transitions, where the interaction between poverty, urbanization, and health systems influences its detection and control (Lönnroth et al. 2009). The theoretical foundation of this research is based on time-series econometrics, specifically the Box-Jenkins methodology for ARIMA modelling (Box & Jenkins 1976). ARIMA is well-suited for handling non-stationary data, making it effective for modelling trends and fluctuations in detection rates over time (Enders, 2014). This approach aligns with established economic modelling principles, which emphasize the importance of capturing temporal dependencies and autocorrelations in data (Stock & Watson 2015).

The conceptual framework of this study focuses on TB case detection rates as the dependent variable, influenced by historical trends modeled through ARIMA. Independent variables include autoregressive (AR) and moving average (MA) components, estimated using conditional least squares (CLS). This framework captures temporal dynamics, enabling accurate forecasts and providing insights into detection trends (Dickey & Fuller 1979; Akaike 1974). By modelling detection rates, this study contributes to evidence-based decision-making and targeted health interventions. Several studies have demonstrated the utility of ARIMA models in disease surveillance (Yadav & Akhter 2021; Siamba et al. 2023).

DATA AND METHODS

This study adopts a quantitative research design, utilizing time-series analysis to model tuberculosis (TB) case detection rates in Uganda from 2000 to 2022. The approach is particularly suited for analyzing temporal data, capturing trends, and making forecasts (Gujarati & Porter 2009). Given the dynamic nature of TB detection rates, the autoregressive integrated moving average (ARIMA) model is selected due to its effectiveness in handling non-stationary data and its capacity to model temporal dependencies (Box et al. 2015). This design enables a systematic examination of historical trends, offering insights for future predictions. The dataset consists of annual TB case detection rates (%, all forms) for Uganda, sourced from the World Bank database (World Bank 2023). The data covers

22 observations (2000-2022), providing a comprehensive representation of TB detection trends over time. Purposive sampling is employed, as the dataset specifically targets TB detection rates, aligning with the research objectives (Creswell 2014). This sampling approach ensures that the data is relevant and sufficient for time-series modelling and analysis.

ARIMA model is employed for time-series forecasting. The methodology involves three key stages: identification, estimation, and diagnostic checking (Box et al. 2015). First, the Augmented Dickey-Fuller (ADF) test is applied to assess stationarity and determine the order of differencing required to achieve stationarity (Dickey & Fuller 1979). Model parameters, including autoregressive (AR) and moving average (MA) components, are estimated using conditional least squares (CLS) due to its robustness in parameter estimation (Hamilton 1994). Model selection is guided by the Akaike Information Criterion (AIC), ensuring optimal balance between model fit and complexity (Akaike 1974). Diagnostic checks are conducted to validate model adequacy, including residual analysis and tests for autocorrelation and normality (Enders 2014). Finally, forecasts for TB detection rates from 2023 to 2032 are generated based on the fitted ARIMA model, providing projections for policy planning and resource allocation. ARIMA (p, d, q) model specification is as follows:

$$Y_t = \mu + \varepsilon_t + \boldsymbol{\phi}_1 Y_{t-1} + \boldsymbol{\phi}_2 Y_{t-2} + \ldots + \boldsymbol{\phi}_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \quad \ldots\ldots\ldots\ldots (1)$$

Where;
Y_t is the value of the series at time t
μ is the mean of the series
ε_t is white noise
$\boldsymbol{\phi}_1, \boldsymbol{\phi}_2, \ldots \boldsymbol{\phi}_p$ are the coefficients of the AR (p) component
$\theta_1, \theta_2, \ldots \theta_q$ are the coefficients of the MA (q) component
p is the order of the autoregressive part, representing the number of past values considered
q is the order of the moving average part, indicating the number of past errors considered
d is the number of differences required to make the series stationary (Box & Jenkins 1976)

Conditional least squares (CLS) estimation is chosen for its efficiency in estimating parameters in time-series models like ARIMA (Greene 2012). By minimizing the sum of squared residuals, CLS provides optimal parameter estimates for modelling tuberculosis case detection rates in Uganda (Box & Jenkins 1976). It is particularly effective for capturing the relationship between observed and predicted values, ensuring accurate forecasts (Hamilton 1994). The CLS estimator for the regression coefficients is given by the following formula:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}}\left[\sum_{t=1}^{n}(y_t - \hat{y}_t(\theta))^2\right]$$

Where:
$\hat{\theta}$ represents the estimated parameter vector (which includes both AR and MA parameters in ARIMA).
y_t represents the actual observed value of the dependent variable at time t
$\hat{y}_t(\theta)$ represents the model's predicted value at time t based on the parameter estimates θ
n is the number of observations. (Greene 2012).

The use of ARIMA modelling in this study is particularly beneficial for modelling tuberculosis (TB) case detection rates, as it enables the evaluation of past behaviors to make reliable projections (Enders 2014). This approach effectively captures the underlying patterns in TB case detection data, providing a robust framework for modelling TB case detection rates in the long run. Moreover, ARIMA's capacity to handle non-stationary data is particularly well-suited to economic time series, where trends and fluctuations exhibit considerable variation over time (Stock & Watson 2015). The analytical rigor of this model supports drawing meaningful, policy-relevant conclusions about Uganda's tuberculosis (TB) case detection rates trajectory, offering insights that can guide effective health policy and planning strategies.

RESULTS

Descriptive statistics (Appendix 1) provide a summary of the key characteristics of the tuberculosis (TB) case detection rates in Uganda from 2000 to 2022. The mean detection rate is approximately 64.74%, indicating that, on average, Uganda's TB detection rates have been below the 100% target set by the World Health Organization (WHO) for effective TB control (WHO 2021). The median value of 63% closely aligns with the mean, reflecting a relatively symmetrical distribution of detection rates over the years. The minimum value of 46% highlights the lowest recorded detection rate, signaling periods of underperformance, while the maximum value of 100% in 2022 suggests recent improvements in detection efforts. However, the standard deviation of 10.55% indicates notable variability in detection rates over the study period, underscoring inconsistent performance (Gujarati & Porter 2009). The skewness value of 1.64 suggests a positive skew, meaning the distribution of detection rates is slightly skewed to the right, with more observations clustered around lower values and fewer observations at higher detection rates. The kurtosis value of 6.92 exceeds the normal threshold of 3, indicating the presence of heavy tails or extreme values in the data, further emphasizing periods of sharp fluctuations (Stock & Watson 2015). The Jarque-Bera statistic of 24.99 and its corresponding p-value of 0.000004 reject the null hypothesis of normality, confirming that the data do not follow a normal distribution (Jarque & Bera 1987). This result justifies the use of the ARIMA model, which does not strictly require normality but focuses on temporal dependencies (Enders 2014).

Stationarity tests (Appendices 2, 3 & 4) are conducted using Augmented Dickey-Fuller (ADF) test to check for stationarity. Results indicate that the original series was non-stationary in level and in first difference ($p > 0.05$). After second difference, the series achieved stationarity ($p < 0.05$), justifying the use of ARIMA model ($d = 2$). ARIMA (1, 2, 1) model is identified as the best, based on Akaike Information Criterion (AIC = 6.714077) and Schwarz Criterion (SC = 6.863437). Parameter estimates include: AR(1) = 0.185933 (p = 0.5673); MA(1) = -0.896946 (p = 0.0008); C = 0.531456 (p = 0.4078). Accordingly, the coefficient of AR(1) is statistically insignificant, that of MA(1) is statistically significant while the constant term is statistically insignificant. Diagnostic checks confirm the adequacy of the model. The residuals are white noise, as confirmed by the Ljung-Box Q test ($p > 0.05$), and the autocorrelation function (ACF) plots show no significant patterns, validating the model's robustness.

Results are summarized as follows:
Results of the ARIMA (1, 2, 1) model (Appendix 5)

$\widehat{TB}_t$ = 0.531456 + 0.185933AR(1) - 0.896946 MA(1) ………….............................… (2)

Hence,

$$\hat{\theta} = \begin{bmatrix} 0.531456 \\ 0.185933 \\ -0.896946 \end{bmatrix}$$

Inferential statistics for the ARIMA (1, 2, 1) model applied to tuberculosis (TB) case detection rates in Uganda provide insights into the relationships between variables, model adequacy, and forecasting reliability. The constant term of 0.531456 represents the baseline level of TB case detection rates when all other factors are zero. However, it is statistically insignificant, meaning it does not have a strong influence on the model's predictions and may not be crucial for explaining variations in TB detection rates (Gujarati & Porter 2009). AR(1) coefficient of 0.185933 is positive but statistically insignificant, suggesting weak evidence of persistence in detection rates over time. This implies that past values have a minimal impact on future rates (Enders 2014).

MA(1) coefficient of -0.896946 is negative and statistically significant, meaning short-term fluctuations or shocks negatively affect detection rates. Suggesting that approximately 90% of the current TB case detection rate is influenced by shocks or errors from the previous period. This highlights the importance of accounting for past errors when modelling detection trends (Box et al. 2015). The Adjusted R-squared value of 0.259513 indicates that approximately 26% of the variation in TB case detection rates is explained by the ARIMA (1, 2, 1) model. While this suggests that the model captures a portion of the variability, the remaining variation may be due to other factors not included in the model (Stock & Watson 2015). The Durbin-Watson statistic of 1.909212 suggests that the residuals are not significantly autocorrelated, as the value is close to 2. This supports the assumption of independent errors, which is critical for the validity of the ARIMA model (Gujarati & Porter 2009).

The histogram of residuals, with a kurtosis value of 3.25 and a Jarque-Bera statistic of 0.055 (p-value 0.972), suggests that the residuals are approximately normally distributed. This normality supports the reliability of the model's

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estimates and predictions (Jarque & Bera 1987). The Ljung-Box Q statistic test results (p = 0.064) indicate that we fail to reject the null hypothesis, meaning the residuals of the ARIMA (1, 2, 1) model are white noise. This implies that no significant patterns remain unexplained by the model, supporting its adequacy for forecasting (Ljung & Box 1978). Further diagnostics confirm that the AR and MA roots are covariance stationary and invertible, as they lie within the unit circle. Covariance stationarity ensures that the model's parameters remain stable over time, making it suitable for forecasting long-term trends (Enders 2014). Finally, the forecasts for 2023-2032 (Appendices 8 and 9) show a gradual improvement in TB detection rates, from 92.3% in 2023 to 95.1% by 2032. However, this still falls short of the 100% detection rate target, highlighting the need for sustained interventions to close the gap (WHO 2021).

DISCUSSION

The findings of this study on modelling tuberculosis (TB) case detection rates in Uganda using the ARIMA (1, 2, 1) model provide important insights into forecasting trends and understanding the dynamics of TB detection. These results are evaluated against previous studies to highlight similarities, differences, and unique contributions to the existing literature.

Previous research has primarily focused on TB prevalence, treatment outcomes, and the effectiveness of interventions rather than predictive modelling. Studies such as Dye et al. (2005) and Diefenbach-Elstob (2018) emphasized the role of detection rates in controlling TB epidemics but did not utilize time-series approaches to predict future trends. Instead, they relied on static estimates and epidemiological projections, which are limited in capturing short-term fluctuations and long-term trends. This study fills that gap by applying an ARIMA model to analyze temporal dynamics and generate forecasts, offering a robust approach to improving TB detection strategies. Similar studies, such as Sabry et al. (2021), employed ARIMA modelling to forecast infectious disease trends, confirming the reliability of this technique for short- and long-term predictions. However, these studies focused on diseases like COVID-19 and influenza, leaving TB detection rates relatively underexplored. This research extends the application of ARIMA modelling to TB surveillance, demonstrating its adaptability and relevance to diverse epidemiological settings.

A key finding of this study is the statistically significant MA(1) coefficient (-0.896946), which highlights the influence of past shocks on current detection rates. Suggesting that approximately 90% of the current TB case detection rate is influenced by shocks or errors from the previous period. Unlike studies by Anwar et al. (2016) that primarily focused on socioeconomic determinants, this research emphasizes the role of historical errors, providing evidence for incorporating dynamic time-series approaches into TB modelling. Adjusted R-squared value (0.259513) indicates that approximately 26% of the variation in TB detection rates can be explained by the ARIMA (1, 2, 1) model. While previous studies, such as Tomov et al. (2023), have achieved higher explanatory power with regression models, this study underscores the importance of modelling residual patterns and forecasting trends rather than solely explaining variability. The diagnostic tests, including the Ljung-Box Q statistic and Durbin-Watson statistic, confirm that the residuals are white noise and free from autocorrelation. These results align with findings by Enders (2014) on time-series modelling, affirming the reliability of ARIMA models for epidemiological forecasting.

Forecasts from this study project a gradual increase in TB detection rates, reaching 95.1% by 2032. However, this remains below the 100% detection target advocated by the World Health Organization (WHO 2021). Unlike studies that assume linear improvements in detection rates, this study reveals persistent gaps, highlighting the need for targeted interventions and resource allocation to address shortfalls. The findings emphasize the importance of integrating predictive analytics into public health planning. While previous approaches focused on retrospective analysis (Diefenbach-Elstob 2018), this study advocates for forward-looking models to anticipate detection gaps and allocate resources effectively. It also underscores the need for continuous data monitoring and model refinement to improve forecasting accuracy and support adaptive policy responses.

LIMITATIONS

While this study provides valuable insights into modelling tuberculosis (TB) case detection rates in Uganda using ARIMA, several limitations are acknowledged. These limitations pertain to the research design, sample size, data quality, and analytical procedures, which may have influenced the findings.

The use of a time-series design limits the scope of this study to historical patterns and trends, potentially overlooking structural and contextual factors that influence TB detection rates (Enders, 2014). For instance, socioeconomic variables, healthcare infrastructure, and intervention programs are not explicitly included in the model, which may restrict its explanatory power (Anwar et al. 2016). Incorporating such covariates in future studies could enhance the robustness of forecasts. The study relies on 22 annual observations (2000-2022), which may be insufficient for capturing long-term patterns or cyclical behaviors in TB detection rates (Gujarati & Porter 2009). Small sample sizes in time-series data often reduce statistical power, making it challenging to identify subtle relationships or trends (Enders 2014). Additionally, missing data for certain years, although addressed through interpolation, may introduce biases or reduce model reliability (Chatfield & Xing 2019).

The ARIMA (1, 2, 1) model assumes linear relationships and stationary processes, which may oversimplify complex dynamics in TB detection rates (Box et al. 2015). Although differencing ensures stationarity, this transformation may lead to information loss, particularly in capturing sudden policy changes or outbreaks (Hyndman & Athanasopoulos, 2018). Furthermore, the conditional least squares (CLS) estimation method, while effective for parameter estimation, can be sensitive to initial values and residual structures (Harvey 1990). The residual diagnostic tests, including Ljung-Box Q statistics and Durbin-Watson tests, confirm model adequacy but do not completely eliminate the risk of model misspecification (Stock & Watson 2015). For example, potential autocorrelation and heteroscedasticity in residuals could undermine forecast precision, particularly for longer horizons (Shumway & Stoffer 2000).

This study focuses exclusively on Uganda, limiting its applicability to other contexts with different healthcare systems, TB prevalence rates, and socioeconomic dynamics (WHO 2021). While the ARIMA approach is generalizable, specific parameter estimates and forecasts may vary significantly across regions, requiring localized calibrations for broader applicability (Sabry et al. 2021). The study's focus on statistical modelling does not account for policy changes, intervention programs, or external shocks, such as the COVID-19 pandemic, which may influence TB detection rates (World Bank 2022). This omission highlights the need for complementary approaches that integrate qualitative and policy analysis to address such factors (Diefenbach-Elstob 2018).

CONCLUSION

This study modelled tuberculosis (TB) case detection rates in Uganda using an ARIMA (1, 2, 1) model estimated through conditional least squares (CLS). The research highlights the persistent challenges associated with suboptimal TB detection rates and underscores the importance of data-driven approaches for forecasting and policy formulation. The findings demonstrate the potential of time-series modelling to capture historical trends and project future detection rates, offering a robust framework for enhancing TB surveillance systems and resource allocation (Hyndman & Athanasopoulos 2018).

The study contributes to the growing body of literature on TB control by addressing the methodological gap in predictive modelling, as prior studies predominantly focused on prevalence and treatment success rates rather than forecasting detection trends (Sabry et al. 2021). The application of ARIMA modelling complements conventional epidemiological methods, enabling policymakers to develop proactive interventions to accelerate TB detection and control efforts (Box et al. 2015). Despite certain limitations, such as the exclusion of structural and policy-related variables, the model's diagnostic tests validate its reliability for forecasting purposes. The study advocates for integrating complementary approaches, including qualitative and policy analysis, to account for socio-economic and healthcare dynamics influencing TB detection rates (Diefenbach-Elstob 2018). Future research should focus on extending the model to incorporate exogenous factors like healthcare infrastructure, funding levels, and intervention programs. Additionally, periodic recalibration of the model will ensure its relevance in addressing Uganda's evolving TB epidemic (Shumway & Stoffer 2000). Strengthening health systems and increasing investments in TB detection programs remain critical to achieving higher detection rates and reducing the disease burden in Uganda.

RECOMMENDATIONS

Based on the findings of this study, several recommendations are proposed to enhance tuberculosis (TB) case detection rates in Uganda. These recommendations address policy formulation, program development, and future research to ensure sustainable improvements in TB detection and control.

Policymakers should prioritize strengthening TB surveillance systems by integrating predictive modelling techniques such as ARIMA into national health monitoring frameworks. This will enhance data analysis capacity and improve forecasting for early detection and intervention (Hyndman & Athanasopoulos 2018). Increased investments in diagnostic facilities and trained personnel are critical to reducing detection gaps and enhancing response times. Policies should focus on expanding access to rural and underserved communities, where TB detection rates remain low (Diefenbach-Elstob 2018). Regular evaluation of TB programs is essential to identify weaknesses and optimize resource allocation. Data-driven policy interventions can help Uganda achieve international targets for TB control, including those outlined in the Sustainable Development Goals (SDGs) (United Nations 2015). Programs should incorporate capacity-building initiatives for health workers to effectively utilize predictive tools and interpret time-series forecasts. This can improve operational efficiency and data utilization (Anwar et al. 2016).

Expanding community-based testing and awareness programs will help address underreporting and stigma associated with TB, particularly in rural areas. Community health workers should be trained to conduct active case finding and follow-ups (Stop TB Partnership 2024). Programs should leverage mobile health technologies and electronic medical records for real-time data collection and reporting. Such systems can streamline patient tracking and facilitate timely interventions (Ahmed et al. 2020). Future research should integrate exogenous variables, including socio-economic factors, healthcare accessibility, and policy shifts, into the forecasting models. This can provide more comprehensive insights into TB detection trends (Shumway & Stoffer 2000). Further studies should explore alternative time-series models, such as vector autoregressive (VAR) models and machine learning algorithms, to assess the robustness and accuracy of forecasts (Box et al. 2015). Future studies should examine TB detection rates across different regions of Uganda to identify localized trends and disparities. Regional analyses will inform targeted interventions and resource distribution (Enders 2014). Additional research should evaluate the impact of specific interventions, such as vaccination programs, drug therapies, and public awareness campaigns, to assess their effectiveness in improving detection rates (WHO 2020).

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APPENDICES

Appendix 1: Descriptive statistics

	TB case detection rate (%, all forms)
Mean	64.73913
Median	63
Maximum	100
Minimum	46
Std. Dev.	10.55383
Skewness	1.637927
Kurtosis	6.917541
Jarque-Bera	24.99176
Probability	0.000004
Sum	1489
Sum Sq. Dev.	2450.435
Observations	22

Appendix 2: Unit root test, TB (in Level)

Null Hypothesis: TB has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.136890	0.9613
Test critical values:	1% level	-3.769597	
	5% level	-3.004861	
	10% level	-2.642242	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TB)
Method: Least Squares
Date: 01/03/25 Time: 13:05
Sample (adjusted): 2 23
Included observations: 22 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TB(-1)	0.026627	0.194511	0.136890	0.8925
C	0.773437	12.36100	0.062571	0.9507

R-squared	0.000936	Mean dependent var	2.454545
Adjusted R-squared	-0.049017	S.D. dependent var	6.441881
S.E. of regression	6.597874	Akaike info criterion	6.697880
Sum squared resid	870.6388	Schwarz criterion	6.797066
Log likelihood	-71.67668	Hannan-Quinn criter.	6.721245
F-statistic	0.018739	Durbin-Watson stat	1.293143
Prob(F-statistic)	0.892486		

Appendix 3: Unit root test, TB (in First difference)

Null Hypothesis: D(TB) has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.395165	0.5626
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations
and may not be accurate for a sample size of 19

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TB,2)
Method: Least Squares
Date: 01/03/25 Time: 13:06
Sample (adjusted): 5 23
Included observations: 19 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TB(-1))	-0.698798	0.500871	-1.395165	0.1833
D(TB(-1),2)	-0.186135	0.408184	-0.456007	0.6549
D(TB(-2),2)	-0.587340	0.333665	-1.760269	0.0987
C	0.984567	1.578353	0.623794	0.5421

R-squared	0.429845	Mean dependent var	0.736842
Adjusted R-squared	0.315814	S.D. dependent var	7.716088
S.E. of regression	6.382402	Akaike info criterion	6.729630
Sum squared resid	611.0258	Schwarz criterion	6.928459
Log likelihood	-59.93148	Hannan-Quinn criter.	6.763280
F-statistic	3.769549	Durbin-Watson stat	1.586510
Prob(F-statistic)	0.033740		

Appendix 4: Unit root test, TB (in Second difference)

Null Hypothesis: D(TB,2) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.987386	0.0009
Test critical values:	1% level	-3.831511	
	5% level	-3.029970	
	10% level	-2.655194	

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations
and may not be accurate for a sample size of 19

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(TB,3)
Method: Least Squares
Date: 01/03/25 Time: 13:06
Sample (adjusted): 5 23
Included observations: 19 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TB(-1),2)	-2.430040	0.487237	-4.987386	0.0001
D(TB(-1),3)	0.776464	0.313777	2.474577	0.0249
C	0.242036	1.529234	0.158273	0.8762

R-squared	0.756453	Mean dependent var	0.368421

Adjusted R-squared	0.726009	S.D. dependent var	12.54862
S.E. of regression	6.568466	Akaike info criterion	6.746377
Sum squared resid	690.3160	Schwarz criterion	6.895499
Log likelihood	-61.09058	Hannan-Quinn criter.	6.771614
F-statistic	24.84781	Durbin-Watson stat	1.733272
Prob(F-statistic)	0.000012		

Appendix 5: Results of the ARIMA (1, 2, 1) model

Dependent Variable: DDTB
Method: ARMA Conditional Least Squares (Gauss-Newton / Marquardt steps)
Date: 01/03/25 Time: 13:19
Sample (adjusted): 4 23
Included observations: 20 after adjustments
Failure to improve likelihood (non-zero gradients) after 20 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 3

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.531456	0.626152	0.848765	0.4078
AR(1)	0.185933	0.318709	0.583395	0.5673
MA(1)	-0.896946	0.218930	-4.096944	0.0008

R-squared	0.337459	Mean dependent var	0.600000
Adjusted R-squared	0.259513	S.D. dependent var	7.535181
S.E. of regression	6.484141	Akaike info criterion	6.714077
Sum squared resid	714.7494	Schwarz criterion	6.863437
Log likelihood	-64.14077	Hannan-Quinn criter.	6.743233
F-statistic	4.329392	Durbin-Watson stat	1.909212
Prob(F-statistic)	0.030221		

Inverted AR Roots	.19
Inverted MA Roots	.90

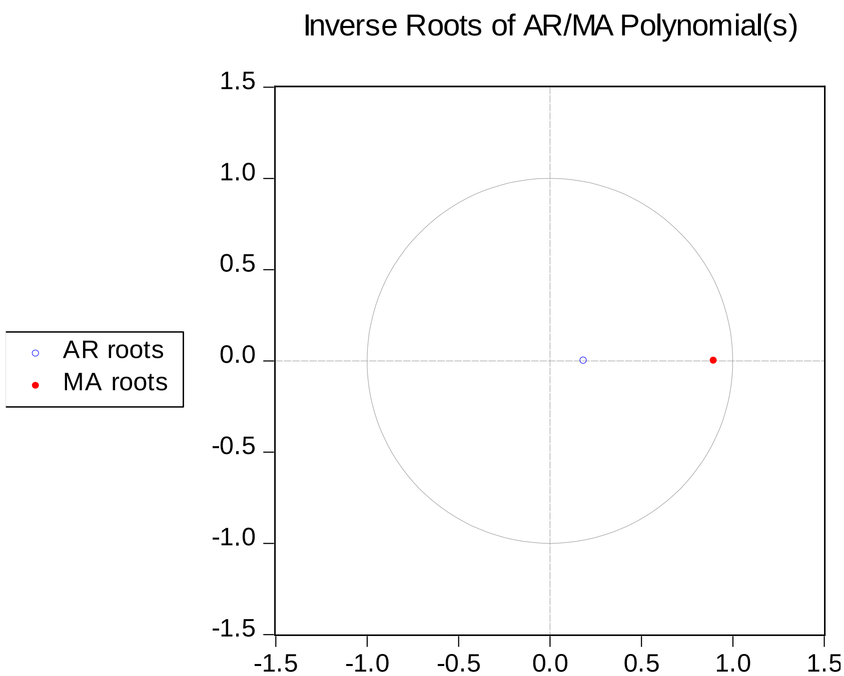
Appendix 6: Ljung-Box Q statistic/ test

Date: 01/03/25 Time: 13:22
Sample: 1 23
Included observations: 20
Q-statistic probabilities adjusted for 2 ARMA terms

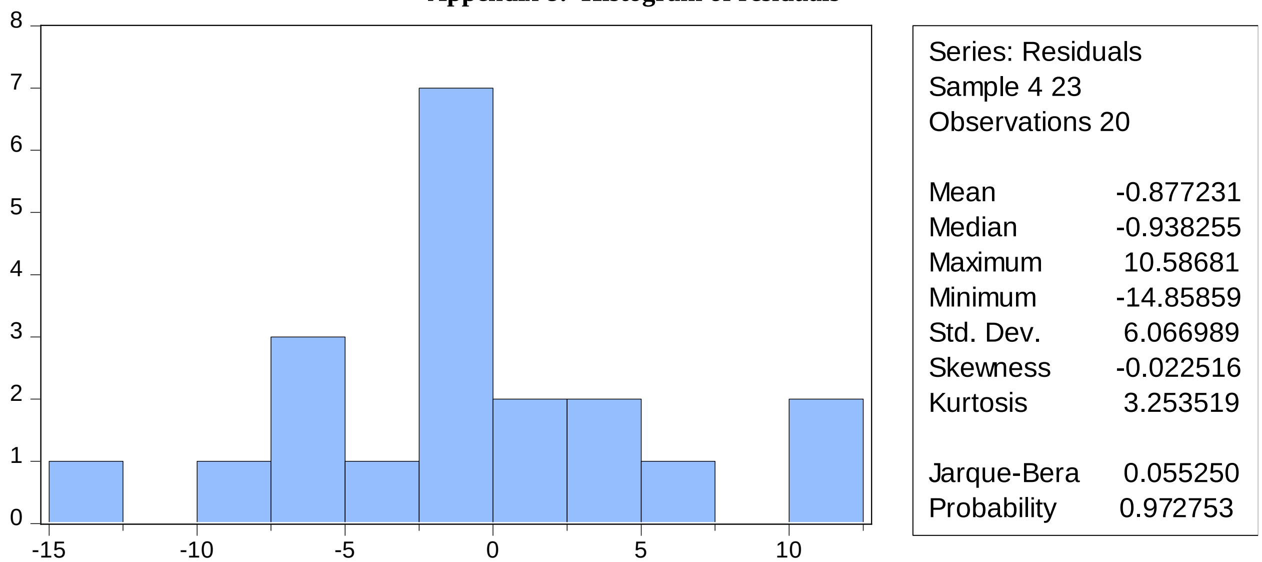
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. *| . |	. *| . |	1	-0.072	-0.072	0.1217	
.**| . |	.**| . |	2	-0.269	-0.276	1.8949	
. |**. |	. |**. |	3	0.243	0.215	3.4204	0.064
. | . |	. *| . |	4	-0.013	-0.066	3.4248	0.180
. |* . |	. |**. |	5	0.108	0.260	3.7691	0.287
. *| . |	. *| . |	6	-0.088	-0.195	4.0113	0.404
. *| . |	. | . |	7	-0.149	-0.022	4.7590	0.446
. |* . |	. *| . |	8	0.086	-0.115	5.0295	0.540
.**| . |	.**| . |	9	-0.216	-0.232	6.8941	0.440
. | . |	. | . |	10	-0.055	-0.042	7.0249	0.534

. |* . |	. | . |	11	0.084	-0.039	7.3710	0.599
. *| . |	. | . |	12	-0.114	0.025	8.0837	0.621

Appendix 7: ARIMA (1, 2, 5) structure



Appendix 8: Histogram of residuals



Appendix 9: Uganda's Tuberculosis case detection rate (%, all forms) FORECAST results

Year	TB case detection rate (%, all forms)	DDTB_FORECAST case detection rate (%, all forms) (in Second difference)	TB case detection rate (%, all forms) (in First difference)
2000	46	NA	46
2001	56	NA	56
2002	62	-4	62
2003	66	-2	66
2004	67	-3	67
2005	63	-5	63
2006	62	3	62
2007	62	1	62
2008	64	2	64
2009	62	-4	62
2010	63	3	63
2011	67	3	67
2012	63	-8	63
2013	63	4	63
2014	60	-3	60
2015	55	-2	55
2016	56	6	56
2017	57	0	57
2018	67	9	67
2019	77	0	77
2020	69	-18	69
2021	82	21	82
2022	100	5	100
2023	NA	-7.749368	92.250632
2024	NA	-1.008226	91.242406
2025	NA	0.245178	91.487584
2026	NA	0.478227	91.965811
2027	NA	0.521559	92.48737
2028	NA	0.529616	93.016986
2029	NA	0.531114	93.5481
2030	NA	0.531392	94.079492
2031	NA	0.531444	94.610884
2032	NA	0.531454	95.142338

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Appendix 9: Graph showing Tuberculosis case detection rate (%, all forms) FORECAST results