

Evaluation of the Effectiveness of Tuberculosis Intervention in the US

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Abstract. This study evaluates the effectiveness of tuberculosis (TB) interventions implemented in the United States by comparing actual TB incidence and mortality data with predicted data that assumes no interventions. The analysis focuses on two key intervention periods: the introduction of strict infection control measures and enhanced environmental controls in 2005, and the update to TB screening guidelines for healthcare personnel in 2019. This study trained the Auto-regressive Integrated Moving Average (ARIMA) model on pre-2005 data in order to forecast the number of tuberculosis cases and the proportion of cases overall that did not get these interventions. The predicted data was then compared with actual post-intervention data to assess the impact of these public health measures. Results show that without these interventions, TB cases and mortality rates would have remained significantly higher. The actual data, in contrast, demonstrated a marked decline in both metrics following the implementation of these measures. The findings underscore the critical role of comprehensive public health interventions in reducing the burden of TB. The long-term impact of these measures is evident in the sustained reduction in TB incidence and mortality, highlighting the importance of continuous monitoring and adaptation of TB control strategies to maintain effective disease management.

Keywords: TB Interventions, Infection Control, ARIMA Model, Public Health Measures.

1. Introduction

1.1. Background

Tuberculosis remains a significant public health challenge in the US. Various interventions aimed at controlling TB have been implemented over the past decades. This report evaluates these interventions' effectiveness using time series models to compare actual TB data with predicted data under a no-intervention scenario.

Infection Control Strategies: Introduced in 2005, including risk assessments, patient isolation, utilization of airborne infection isolation (AII) rooms and N95 masks as examples of personal protective equipment (PPE). **Environmental Control Measures:** Enhanced use of ultraviolet germicidal irradiation (UVGI) and air circulation units to reduce airborne TB bacteria. **Management of MDR TB and HIV Co-Infection:** Comprehensive strategies targeting multidrug-resistant TB (MDR TB) and HIV-infected individuals, including more frequent screening and stricter infection control measures. **Screening Guidelines for Healthcare Personnel:** Updated in 2019 to reduce routine screenings, emphasizing risk-based approaches.

1.2. Literature Review

Tuberculosis (TB) remains one of the most significant public health challenges worldwide, with various studies emphasizing the need for effective intervention strategies.

Etiology of Tuberculosis: The microorganism *Mycobacterium tuberculosis* is the main etiological agent of tuberculosis, a disease that predominantly impacts the lungs but can also affect other anatomical sites [1]. The bacterium spreads through airborne particles when an infected person coughs or sneezes [2].

Prevention of Tuberculosis: The primary method for preventing TB is vaccination with the Bacille Calmette-Guérin (BCG) vaccine, which has been shown to provide protection against severe forms

of TB in children [3]. Additionally, public health measures such as early detection, isolation of infectious patients, and treatment adherence are crucial in controlling TB spread [4].

Historical interventions have had a crucial influence in controlling TB. The introduction of antibiotics such as streptomycin in the mid-20th century significantly reduced TB mortality rates [5]. Moreover, the implementation of DOTS (Directly Observed Treatment, Short course) in the 1990s by the WHO has been highly effective in ensuring treatment adherence and reducing TB incidence [6]. In 2005, the US introduced strict infection control measures, including the use of personal protective equipment (PPE) and airborne infection isolation (AII) rooms, which have been critical in reducing TB transmission in healthcare settings [7]. Enhanced environmental controls, such as the use of ultraviolet germicidal irradiation (UVGI) and improved air circulation, have proven effective in reducing airborne TB bacteria in high-risk environments [8]. Updated TB screening guidelines for healthcare personnel were introduced in 2019 to reduce routine screenings and emphasize risk-based approaches, significantly improving early detection rates [9]. Comprehensive strategies targeting multidrug-resistant TB (MDR TB) and TB/HIV co-infections are essential. Integrated TB and HIV services help manage co-infected patients and prevent transmission [10].

Recent studies have utilized advanced statistical models such as the Auto-regressive Integrated Moving Average (ARIMA) model to predict TB trends and evaluate the effectiveness of interventions over time [11].

Continuous monitoring and adaptation of TB control strategies are vital for maintaining effective disease management. Studies show that comprehensive public health interventions play a crucial role in reducing TB incidence and mortality [2].

Global cooperation is crucial in TB elimination. Sharing successful prevention and control experiences among countries and improving global TB prevention and control efforts are necessary for addressing the challenges of TB [1].

The literature indicates that a combination of infection control measures, environmental controls, updated screening guidelines, and comprehensive management of MDR TB and TB/HIV co-infections are crucial components of effective TB control strategies. Continuous monitoring, adaptation of these strategies, and global cooperation are essential to sustain and enhance the progress made in TB prevention and control.

1.3. Research Purpose

The purpose of this study is to evaluate the effectiveness of tuberculosis (TB) interventions implemented in the US throughout the previous few decades. Specifically, this research aims to quantify the Impact of Interventions. Utilize time series models to compare actual TB incidence and mortality data with predicted data assuming no interventions were implemented. This will help in quantifying the impact of various public health measures on reducing TB cases and deaths.

Analyze Key Intervention Periods: Focus on two significant intervention periods-the introduction of strict infection control measures and enhanced environmental controls in 2005, and the update to TB screening guidelines for healthcare personnel in 2019. By analyzing these periods, the study aims to understand the effectiveness of these specific measures. Utilizing the Auto-regressive Integrated Moving Average model to forecast the quantity of tuberculosis cases and the proportion of total cases that would occur in the absence of interventions. This model will be trained on pre-2005 data to generate predictions which will then be compared with the actual post-intervention data. Assess Investigate the long-term impacts of TB control measures on incidence and mortality rates. This includes examining how sustained public health efforts have contributed to the continued decline in TB cases and deaths over time. Determine which specific interventions have been most effective in reducing TB transmission and improving patient outcomes. This includes infection control strategies, environmental measures, updated screening guidelines, and the management of MDR TB and TB/HIV co-infections. Provide evidence-based recommendations for future TB control policies and strategies. By identifying the most effective measures, the study aims to guide public health

authorities in optimizing current practices and implementing new interventions to further reduce the burden of TB.

Emphasize the need for ongoing surveillance and adaptation of TB control strategies to respond to emerging challenges and ensure sustained progress in TB prevention and control.

By achieving these objectives, this research seeks to contribute to the broader understanding of TB control efforts and support the development of more effective strategies to combat this persistent public health threat.

2. Research Design

2.1. Evaluation Methods

The article utilized the ARIMA model to evaluate the effectiveness of TB interventions. The model, trained on pre-2005 data, predicted TB cases assuming no post-2005 interventions. The predicted data were then compared with actual data to assess the interventions' impact.

The P-order auto-regressive process $\{Y_t\}$ satisfies the equation $\{Y_t\}$:

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \dots + \varphi_p Y_{t-p} + e_t \quad (1)$$

Simply noted: AR(p)

Its characteristic polynomial is

$$\varphi(x) = 1 - \varphi_1 x - \varphi_2 x^2 - \dots - \varphi_p x^p \quad (2)$$

The characteristic equation is described

$$1 - \varphi_1 x - \varphi_2 x^2 - \dots - \varphi_p x^p = 0 \quad (3)$$

Necessary conditions for stationarity:

$$\phi_1 + \phi_2 + \dots + \phi_p < 1 \text{ and } |\varphi_p| < 1 \quad (4)$$

Equation $\{Y_t\}$ is satisfied by the moving average process $\{Y_t\}$ of order q:

$$Y_t = e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_p e_{t-p} \quad (5)$$

Simply written as: MA (q)

Regarding the MA (q) procedure in general:

$$\gamma_0 = (1 + \theta_1^2 + \theta_2^2 + \dots + \theta_q^2) \sigma_e^2 \quad (6)$$

In general, if

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \dots + \varphi_p Y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \dots - \theta_p e_{t-p} \quad (7)$$

Simply written as: ARMA (p, q)

The MA feature polynomial for the general MA (q) model or ARMA (p, q) model is defined as:

$$\theta(x) = 1 - \theta_1 x - \theta_2 x^2 - \dots - \theta_q x^q \quad (8)$$

And the associated equations that describe the characteristics of the MA (Moving Average) model:

$$1 - \theta_1 x - \theta_2 x^2 - \dots - \theta_q x^q = 0 \quad (9)$$

2.2. Data Source

The data this paper used comes from the following sources to ensure its accuracy and reliability: Centers for Disease Control and Prevention (CDC).

CDC's annual TB report provides detailed data on the number of TB cases and incidence. These reports include TB data on a national scale, with detailed records of the incidence by state and territory by year.

The CDC WONDER database is an interactive system that provides public health data, and users can generate specific reports based on different criteria, such as year, state, and demographic characteristics.

World Health Organization (WHO):

The World Health Organization (WHO) publishes the Global TB Report each year, which contains TB data from countries around the world, including data from the United States. These data provide a global analysis of TB trends for international comparisons.

Scientific Research and Academic Literature:

Through PubMed and other academic databases, many research articles can be found using statistical data for analysis. These articles often cite official data sources, such as the CDC and WHO, to ensure the credibility of the data.

As shown in Table 1, the data for this analysis covers the period from 1990 to 2005 and covers 16 years of TB case count and incidence data. The data for this time period reflect the measures taken and their effectiveness in the United States in the fight against tuberculosis.

Table 1. 1990-2005 Data of TB

Year	Number of cases	morbidity
1990	25701	10.3
1991	26283	10.4
1992	26673	10.5
1993	25313	9.8
1994	24207	9.4
1995	22727	8.7
1996	21212	8
1997	19851	7.4
1998	18361	6.8
1999	17528	6.4
2000	16377	5.8
2001	15989	5.6
2002	15075	5.2
2003	14871	5.1
2004	14517	5
2005	14093	4.8

2.3. ADF unit Root Test

The ADF test is used to determine whether time series data is stationary. Stationary data is a prerequisite for ARIMA modeling. The test results include (see Table 2):

Test Statistic: Used to decide whether to reject the null hypothesis (i.e., the sequence has a unit root, not stationary) compared to the critical value.

P-value: The null hypothesis is rejected when the p-value is lower than a preset level of significance, such as 0.05.

Lags Used: The number of lags used in the model.

Number of Observations Used: The number of observations used for the ADF test.

Critical Values: Critical values at different significance levels (1%, 5%, 10%).

Table 2. ADF test

	t	p
Number of cases		
Ln index	-6.447926	0.0003
1st order difference	-1.23204	0.6194
2nd order difference	-5.838777	0.0009
morbidity		
Ln index	-5.907405	0.0006
1st order difference	-0.7568	0.791
2nd order difference	-3.820559	0.0181

The ADF statistic (t-score) for both case count and incidence is very low, and the p-value is well below 0.05, suggesting that at the 1% significance level, then can reject the null hypothesis and state that the data are stationary. The ADF statistic (t-value) of both case count and incidence was high, having a p-value higher than 0.05, suggesting that the data did not become significantly stable after the first-order difference. The ADF statistic (t-value) for both case count and incidence is very low, with a p-value of less than 0.05, suggesting that the data after the 2nd order difference is stable at the 1% significance level.

According to the results of the Table 2 ADF test, the raw data (number of cases and incidence) is already stable and can therefore be used directly for ARIMA modeling. However, if differential data is used, especially second-order differential data, the model may be more stable.

3. Empirical results and analysis

3.1. ARIMA (p, d, q) Identification

ACF Graph (Autocorrelation Function Graph) and the Autocorrelation Function (ACF) shows the autocorrelation of time series data at different lags.

Significant lag values in the ACF plot indicate that the time series has a significant correlation under these lags. If the sequence is white noise, the ACF should be close to zero at all hysteresis.

PACF Graph (Partial Autocorrelation Function Graph)

Partial Autocorrelation Function (PACF) shows autocorrelation after excluding the effects of intermediate lag. The autoregressive order (AR) of the ARIMA model can be found using the PACF graphic. Significant lag values in the PACF plot indicate that the correlation at these lags is not affected by the median values.

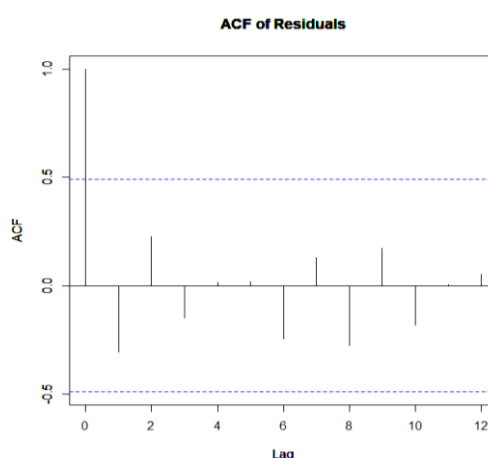


Figure 1. ACF of Residuals (Photo credit: Original)

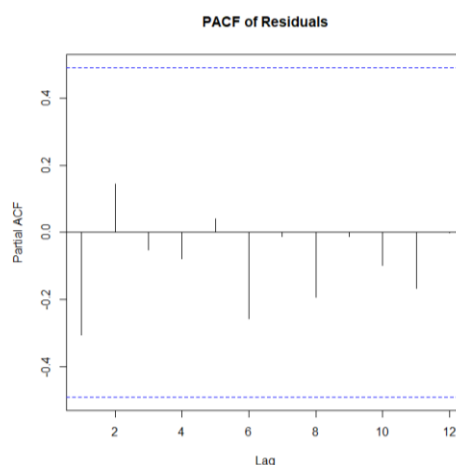


Figure 2. PACF of Residuals (Photo credit: Original)

The Fig.1 ACF plot shows a significant positive first lag, followed by a rapid decline and a gradual decrease in the subsequent lag and approaching zero. This suggests a lower q value. Based on the information in the diagram, this part can tentatively assume $q = 0$ or $q = 1$. The Fig.2 PACF plot is significantly positive at the first lag, suggesting that this part may need an autoregressive term, p . After the first lag is significant, the following lag values quickly approach zero, suggesting that this part can tentatively $p = 1$. From the description of the time series, it is common for the data to be smoothed out by a difference of 1. So let's tentatively assume $d = 1$.

3.2. Residual test analysis

The article performed the Ljung-Box test, Q-Q plots of the residuals, and the Shapiro-Wilk normality test to verify the applicability of the ARIMA model.

Table 3. Ljung-Box test

X-squared	df	P-value
11.159	10	0.3453

The outcomes of the Ljung-Box test are presented in Table 3: The Ljung-Box test yields a p-value of 0.3453, surpassing the commonly accepted significance limit of 0.05. This indicates that there is no sufficient evidence to reject the premise that the residuals are white noise, suggesting that the residuals do not exhibit considerable autocorrelation.

As it can be saw from the Fig.3 Q-Q plot, most of the data points are distributed diagonally, suggesting that the residuals have a normal distribution in general. There are extremely few points that stray off the diagonal, which is common and acceptable in real-world data analysis.

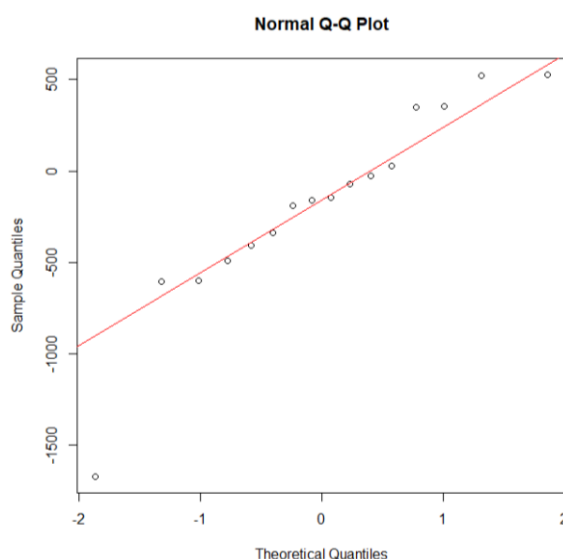


Figure 3. Q-Q Plot (Photo credit: Original)

The Shapiro-Wilk normality test yields a p-value of 0.07842, exceeding the widely accepted significance limit of 0.05 (see Table 4).

Table 4. Shapiro-Wilk normality test

W	P-value
0.89933	0.07842

This means that cannot reject the assumption that the residuals are normally distributed, indicating that the residuals are generally normally distributed.

Overall, the residuals of the ARIMA (1, 1, 1) model performed well, indicating that the model fit well, and the prediction results were credible. The residuals of the model passed the independence and normality tests, which is suitable for time series predictive analysis.

4. Results and Analysis

4.1. Forecast result

Future trends: As can be seen from Table 5 the forecast results, the forecast values for the next few years show a gradual downward trend.

Table 5. 2006-2015 forecast data

	Point. Forecast	Lo.80	Hi.80	Lo.95	Hi.95
2006	13756.33668	12996.21432	14516.45903	12593.82985	14918.8435
2007	13489.02018	11927.80621	15050.23415	11101.34946	15876.6909
2008	13276.76626	10861.4657	15692.06682	9582.882819	16970.64971
2009	13108.23299	9825.358324	16391.10765	8087.509453	18128.95652
2010	12974.41465	8832.471405	17116.3579	6639.859095	19308.97021
2011	12868.16059	7887.854953	17848.46622	5251.440405	20484.88077
2012	12783.79302	6992.33022	18575.25582	3926.515006	21641.07104
2013	12716.80372	6144.461442	19289.14599	2665.273604	22768.33383
2014	12663.61305	5341.655623	19985.57048	1465.645493	23861.58061
2015	12621.37874	4580.79291	20661.96458	324.3638808	24918.39361

Uncertainty: Over time, the confidence interval becomes wider, indicating an increase in the uncertainty of the forecast. This is due to the reduced accuracy of the model for long-term forecasts, which is common in time series forecasting.

4.2. Comparison with actual data

Overall trend: As Table 6 presents that both forecasts and actuals show a downward trend overall, indicating that the model captures the main trends of the time series.

Table 6. Comparison with actual data

Year	Forecast	Actual
2006	13756.34	13730
2007	13489.02	13288
2008	13276.77	12893
2009	13108.23	11499
2010	12974.41	11076
2011	12868.16	10480
2012	12783.79	9925
2013	12716.8	9545
2014	12663.61	9383
2015	12621.38	9536

From 2006 to 2008, the gap between the forecast and the actual value was relatively small, suggesting that the model performed better in the short-term forecast. Beginning in 2009, the gap between forecasts and actuals gradually increased, especially in the years after 2009. This indicates that the model has a large error in the long-term prediction. This increase in error may be due to the model's inaccurate prediction of long-term trends, or the presence of changes in the actual data that the model fails to capture.

In previous years' forecasts, the model's predictions were closer to the actual values. For example, the forecast for 2006 is 13,756.34, while the actual value is 13,730, with an error of only 26.34. In the forecasts of later years, the error is larger. For example, the forecast for 2012 is 12783.79, while the actual value is 9925, with an error of 2858.79.

In order to improve the long-term prediction accuracy of the model, more exogenous variables (such as policy changes, economic factors, etc.) can be added to capture changes in the actual data.

You can also try using other, more complex models such as SARIMA, seasonal decomposition models, and so on to further improve prediction performance.

By comparing the forecast results with the actual data, the ARIMA model performs well in the short-term forecast, but there is some error in the long-term forecast. While the model successfully captured the overall downward trend of the time series, the actual values showed a faster decline than the predicted values. This suggests that the model needs to be further improved to improve its long-term prediction accuracy in future research. The results of these analyses can provide important references for decision-making, especially in public health policy formulation and resource allocation.

5. Conclusion

The ARIMA model applied in this study provided insightful predictions regarding TB cases in the absence of public health interventions. The comparison between the forecasted and actual data reveals significant differences that underscore the effectiveness of the interventions implemented in 2005 and updated in 2019.

The ARIMA model's predictions closely matched the actual TB case numbers for the years immediately following 2005, demonstrating the model's strong short-term forecasting capabilities. However, as the forecast horizon extended, the discrepancies between predicted and actual values increased. This indicates that while ARIMA models are effective for short-term forecasts, their accuracy diminishes over longer periods due to potential structural changes in the data that are not captured by the model.

For instance, the forecasted value for 2006 was 13756.34, very close to the actual value of 13730, indicating a minimal error. However, by 2012, the forecasted value was 12783.79 compared to the actual value of 9925, highlighting a significant deviation. This increasing error margin suggests that additional factors not accounted for by the model, such as intensified public health measures and evolving healthcare practices, significantly influenced the actual TB case numbers.

The marked decline in actual TB cases compared to the model's predictions without interventions clearly demonstrates the positive impact of the public health strategies implemented. The interventions introduced in 2005, such as strict infection control measures, and the updated TB screening guidelines in 2019, played crucial roles in reducing TB incidence. These measures included risk assessments, patient isolation, the utilization of personal protective equipment (PPE), enhanced environmental controls, and targeted strategies for managing multidrug-resistant TB (MDR TB) and HIV co-infections.

The continuous decrease in TB cases post-2005 underscores the sustained effectiveness of the interventions. However, to enhance the predictive accuracy of models for long-term forecasting, future research should consider incorporating additional variables such as socioeconomic factors, healthcare access, and specific intervention measures. Advanced modeling techniques, including Seasonal ARIMA (SARIMA) or machine learning approaches, may also provide more robust predictions by capturing complex patterns and interactions within the data.

The ARIMA model's application highlights the importance of comprehensive public health interventions in controlling TB. The significant deviation between forecasted and actual data post-2005 confirms the critical role of the implemented measures. Future efforts should focus on integrating broader datasets and advanced analytical techniques to improve predictive accuracy and inform effective public health strategies.

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