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Forecasting GDP Growth in Sri Lanka: Dynamic Insights from Harvey-Type Time Series Decomposition Models

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Abstract

This study aims to enhance the accuracy of GDP growth forecasting in Sri Lanka by evaluating structural time series decomposition models, with a focus on Harvey-type models that incorporate intervention analysis. Despite the importance of reliable forecasts for economic planning, limited studies have applied these models to GDP data in the Sri Lankan context. Addressing this gap, the study utilises quarterly GDP growth rates from 2000 to 2023, sourced from annual reports of the Central Bank of Sri Lanka. A range of Harvey-type structural time series specifications were examined, with model performance assessed using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Akaike's Information Criterion (AIC), Bias-corrected AIC (AICc), and Bayesian Information Criterion (BIC). The chosen model incorporates time-varying level and trend along with intervention terms to account for external shocks. Forecasts for the four quarters of 2024 closely matched actual values, with predicted GDP growth rates of 5.279%, 4.652%, 5.445%, and 5.128%, compared to actuals of 5.3%, 4.7%, 5.5%, and 5.3%, respectively. The results confirm the model's robustness and the resurgence of the agriculture, industry, and service sectors in Sri Lanka's post-crisis economy. This research highlights the flexibility and predictive strength of Harvey-type structural time series models with intervention analysis. It recommends their adoption for economic forecasting in Sri Lanka, particularly under conditions of volatility, thereby offering a valuable tool for policymakers and stakeholders engaged in forward-looking economic planning.

Keywords: Dynamic forecasting, GDP growth, Harvey-type models, Intervention analysis, Time series decomposition

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INTRODUCTION

Economic growth is the primary concern of the development and stability of a country or a nation's economy. GDP growth rates are often considered the most widely recognised indicator of economic performance (Romer, 1990; Barroe, 1991; Fioramonti, 2013; Mankiw, 2018). It provides invaluable information for policymakers, stakeholders, investors, and businessmen to make expert decisions. It also reveals whether an economy is expanding or contracting, comparing to different periods and with other economies (Costanza et al., 2009; International Monetary Fund, 2024; Organisation for Economic Co-operation and Development [OECD], 2024). Though GDP growth is a crucial measure of economic performance, it limits its uses as an indicator of economic welfare (Costanza et al., 2009; Fioramonti, 2013).

Accurate forecasting of GDP growth rates is crucial since the Sri Lanka's economic growth trajectory has encountered multiple challenges, including internal and external shocks such as the global financial crisis, domestic political unrest, the COVID-19 pandemic, and the devaluation of the local currency. Sri Lanka has faced significant disturbance in growth due to these interruptions. These disturbances have created erratic oscillations of GDP growth and exacerbated the challenges with consistent forecasting. Therefore, it is important to identify robust and adaptive statistical or econometric models to capture the complexities of high volatile economic data.

The Central Bank of Sri Lanka [CBSL] (2022) pointed out that the frequent oscillations of GDP growth have driven inconsistent economic predictions. One of the key highlights in Sri Lanka's economic growth trajectory was the significant favourable growth of 8% in 2010. The growth of GDP has shown a promising economic future. However, the sustainability of this momentum was difficult, resulting a decline in GDP growth to 4.2% by 2015. The decline further worsened with a contraction of -4.6% in 2020, reflecting the severe impacts of the global pandemic and political unrest experienced during that period. By 2022, GDP growth dropped further to -7.6%. The depreciation of the Sri Lankan rupee and a severe debt crisis caused the decline. These challenges have aggravated financial instability, placing significant pressure on the government and problematising efforts to achieve steady and sustainable economic growth. In such a context, the accuracy of the GDP forecasts is critical for facilitating economic recovery, resource allocation, and long-term sustainable development.

Steady of economic growth allows policymakers, stakeholders and forecasters to make steady decisions in their policy agendas. However, the unstable fluctuations in recent GDP growth rates in Sri Lanka create significant uncertainty about the

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future. The wobbly nature of the current economy and crippling dependency on debt has sharpened this uncertainty. Consequently, forecasting the GDP growth rate in Sri Lanka is a strenuous challenge due to the dynamic nature of economic variables and the limited amount of recent research in this area. Therefore, this study aims to address this research gap by predicting future GDP growth rates in the Sri Lankan economy. This study enables researchers to explore the predictive power of the time series decomposition approaches for highly volatile economic variables.

In the context of forecasting, time series techniques provide valuable theoretical frameworks for understanding historical patterns and predicting the future. Time series forecasting techniques involve different types of models including simple naïve forecasting to advanced models such as ARIMA-X with interventions. Furthermore, it has been shown that different time series specifications perform best in different contexts. Therefore, the current study proposes to conduct a comparative analysis of the time series decomposition specifications by considering the data properties and the behaviour of the time series intended to be analysed.

The paper is divided into several sections as follows: Section 2 provides an in-depth comparative discussion of the existing literature on forecasting techniques emphasising time series decomposition methods. Section 3 describes the overall research methodology adopted in the investigation, focusing on the different specifications of Harvey-type structural decomposition models. This section further provides criteria used for model evaluation. Section 4 provides a comparative and comprehensive discussion of the results and findings. Finally, the paper concludes with remarks and consults for future recommendations of the research.

LITERATURE REVIEW

Several forecasting procedures are available in the literature, ranging from simple naïve forecasting and smoothing techniques to more advanced statistical models such as state space and intervention time series models. This investigation explicitly examines the use of decomposition techniques. Time series forecasting provides a powerful framework for economic prediction by exploiting the underlying structure and components of time series data. Among various approaches, time series decomposition has gained prominence in economic forecasting due to its ability to separate a series into trend, seasonal, and irregular components.

A range of decomposition techniques has been developed over time, including classical decomposition, X-11, X-12-ARIMA, X-13-ARIMA-SEATS, and STL (Seasonal-Trend Decomposition using LOESS). These

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methods vary in flexibility and effectiveness across different data conditions. Hyndman and Athanasopoulos (2021) emphasis that decomposition techniques like classical, STL, and X-12 ARIMA remain essential tools for economic forecasting. Comparative studies, such as those by Makridakis et al. (1998), underscore the importance of evaluating forecasting methods under various conditions. Cleveland et al. (1990) introduced STL as a robust alternative to classical decomposition, and subsequent empirical applications by Theodosiou (2011) and Dudek (2023) further confirm its utility. These decomposition approaches are valuable for their simplicity, yet they often lack the flexibility to model time-varying structures or incorporate external shocks.

Recent advancements have led to the development of Harvey-type structural time series models, which represent a significant evolution in decomposition-based forecasting. Introduced by Harvey (1985, 1986, 1989) and further developed in collaboration with others (Harvey & Peters, 1990; Harvey & Koopman, 1992), these models use a state space framework and Kalman filtering to estimate unobserved components dynamically. Their ability to allow time-varying trends, seasonal components, and stochastic cycles offers a richer, more adaptive modeling approach. A key enhancement to structural time series models is intervention analysis, which allows the incorporation of sudden external events—such as economic shocks, policy changes, or global crisis-directly into the forecasting framework (Harvey, 1996; Song et al., 2011; Koopman et al., 2016). This integration provides more accurate forecasts in volatile environments and facilitates better understanding of how interventions impact the dynamic evolution of economic variables.

Despite their advantages, the empirical application of Harvey-type models with intervention analysis remains limited. While studies such as Sridharan et al. (2003) and Kapetanios et al. (2019) demonstrate their potential, few have applied these models in the context of GDP forecasting. This represents a significant gap in the literature, particularly in developing economies like Sri Lanka, where the economy is subject to frequent structural changes and volatility.

GDP forecasting using time series methods has been widely explored in global literature (Eftimoski, 2019; Gupta & Minai, 2019; Dovern, 2013; Bäurle et al., 2021). However, in the Sri Lankan context, existing studies are scarce. Studies by Ranasinghe and Suriyaarachchi (2015), Dilhani (2017), and Jeyarajah (2022) have employed traditional time series models for GDP prediction. While these studies offer useful insights, they rely on older techniques that lack the flexibility to capture time-varying structures or accommodate internal and external shocks—factors that are increasingly critical in the post-crisis economic climate of Sri Lanka. In recent years, Sri Lanka has experienced significant economic instability characterised by sharp GDP contractions, currency depreciation, and external debt crises. Under such conditions, it is crucial to employ forecasting models that can reflect the dynamic, non-stationary nature of economic data and account for structural breaks. However, existing local studies do not incorporate intervention analysis or utilise Harvey-type structural decomposition, making their forecasts less reliable under current macroeconomic volatility.

This study addresses this clear research gap by applying Harvey-type structural time series models with intervention analysis to forecast quarterly GDP growth rates in Sri Lanka. By evaluating different model specifications and integrating unexpected shocks into the analysis, the research aims to produce more accurate and policy-relevant forecasts. The findings are expected to enhance the understanding of GDP dynamics and offer a practical forecasting tool for economic planning and decision-making.

RESEARCH METHODOLOGY

The current study depends on secondary data comprising 96 observations of quarterly GDP growth rates in Sri Lanka from 2000 to 2023. The relevant data are available in the annual reports of the CBSL. Since there are anomalies in the data, additional treatments, including intervention time series specifications are necessary. Computational procedures are facilitated by the software Time Series Lab (Lit et al. 2022). Descriptive statistics provides a deep understanding of the data exploring inherited characteristics. Some time series-specific graphical tools, particularly seasonal sub-series plots, enhance the comprehensive knowledge of the behaviour of the data. Inferential statistical procedures like the Shapiro-Wilk test strengthen forecasting endeavours.

Harvey-Type Structural Time Series Models (Harvey-Type STM)

The present study employs Harvey-type structural time series models with intervention analysis to forecast quarterly GDP growth in Sri Lanka. This modelling approach is particularly well-suited to the research objective, which is to produce accurate and robust forecasts under conditions of economic volatility. Unlike traditional models such as ARIMA or classical decomposition, structural time series models can accommodate time-varying levels, trends, and seasonal patterns, making them more adaptable to the dynamic nature of macroeconomic data. The Kalman Filter-based state space framework provides a flexible estimation mechanism and allows decomposition into interpretable components. Moreover, the integration

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of intervention analysis enables the model to incorporate the effects of external shocks, such as policy changes or economic crises—factors highly relevant in the context of Sri Lanka's recent economic instability. This methodology has been validated in prior research (Harvey, 1989; Koopman et al., 2016), and its application in forecasting GDP growth remains relatively underexplored in Sri Lanka. Therefore, this technique not only aligns with the research goals but also fills a significant methodological gap in local economic forecasting literature.

Structural time series decomposition is analogous to the classical time series models that decompose the time series into trend, seasonal and irregular components. Harvey-type structural time series model is more flexible and adjustable for different forecasting situations (Harvey, 1985; 1989). The following section presents the variations of the structural time series models.

Local level model

Observation equation:

$$y_t = \mu_t + \varepsilon_t \qquad where\ \varepsilon_t \sim (0, \sigma_\varepsilon^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$State - spce\ equation$:

$$\mu_t = \mu_{t-1} + \eta_t, \quad where\ \eta_t \sim \left(0, \sigma_\eta^2\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Local linear trend model

Observation equation:

$$y_t = \mu_t + \varepsilon_t \qquad where\ \varepsilon_t \sim (0, \sigma_\varepsilon^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$State - spce\ equations$:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t, \quad where\ \eta_t \sim \left(0, \sigma_\eta^2\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

$$\beta_t = \beta_{t-1} + \zeta_t, \qquad where\ \zeta_t \sim \left(0, \sigma_\zeta^2\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Local cubic trend model (third-order trend)

Observation equation:

$$y_t = \mu_t + \varepsilon_t \qquad where\ \varepsilon_t \sim (0, \sigma_\varepsilon^2) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

$State - spce\ equations$:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \frac{1}{2}\gamma_{t-1} + \frac{1}{6}\psi_{t-1} + \eta_t \quad where\ \eta_t \sim N\left(0, \sigma_\eta^2\right) \ldots\ldots\ldots\ldots (7)$$

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$$\beta_t = \beta_{t-1} + \gamma_{t-1} + \frac{1}{2}\psi_{t-1} + \zeta_t, \quad where\ \zeta_t \sim N\left(0, \sigma_\zeta^2\right) \ldots\ldots\ldots\ldots\ldots\ldots (8)$$

$$\gamma_t = \gamma_{t-1} + \psi_{t-1} + \xi_t, \quad where\ \xi_t \sim N\ \left(0, \sigma_\xi^2\right) \ldots\ldots\ldots\ldots\ldots\ldots (9)$$

$$\psi_t = \psi_{t-1} + \kappa_t, \quad where\ \kappa_t \sim N(0, \sigma_\kappa^2) \ldots\ldots\ldots\ldots\ldots\ldots (10)$$

Local cubic trend with interventions

Observation equations:

$$y_t = \mu_t + \omega I_t + \varepsilon_t \quad where\ \varepsilon_t \sim (0, \sigma_\varepsilon^2) \ldots\ldots\ldots\ldots\ldots\ldots (11)$$

$$I_t = \begin{cases} 1 & if\ t > t_0 \\ 0 & otherwise \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (12)$$

Where, y_t is the observed time series at time t, μ_t represents the trend component, β_t is the slope (velocity), γ_t represents the acceleration, ψ_t is the Jerk (rate of change of acceleration), ω is the effect size of intervention ε_t is irregular random component (observation error) which assumes a white noise condition, η_t is the level disturbance, ζ_t is the slope disturbance, ξ_t is the acceleration disturbance and κ_t is the jerk disturbance.

The estimation procedure of the model entirely depends on the maximum likelihood method where Kalman-filter also uses for the estimation and local level smoothing. It provides flexibility to handle different components in a structural time series models. For example, level, slope and seasonal components may be fixed or time-varying. It is not suitable fixed components models since those components are time varying in practice. Therefore, this study suggests employing the time-varying approach to the structural time series forecasting.

Further, modelling task will allow for intervention events or outliers. Kalman-filtering enables smoothing process.

The negative impact of Covid 19 and economic crisis depicts extreme outliers and therefore, the model requires intervention components accommodating the effect. Accordingly, the model given in equation (13) is estimated in empirical analysis.

$$y_t = \mu_t + \psi_1 I_{1t} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (13)$$

Detection of Seasonality Using Dummy Variable Regression

To preliminarily identify the presence and pattern of seasonality in the quarterly GDP growth series, a dummy variable regression approach was employed. This method involves regressing the GDP growth rates on a set of seasonal dummy variables that represent each quarter, allowing for the isolation of seasonal effects from the

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trend and irregular components. The model specification is given in equation (14).

$$GDP_t = \alpha + \beta t + \sum_{i=2}^{4} \delta_i D_i + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots (14)$$

Where, GDP_t represents GDP growth rate at time t, D_i is the respective dummy variable for each season and it measures average GDP growth rate in the season S. The regression coefficients α, β, δ, denote different effect sizes while ε_t is the usual stochastic disturbance term. Ordinary least squares (OLS) method provides the estimation mechanism for these regression models.

Model Adequacy

A detailed comparative analysis enables researchers to investigate the best-performing models. Mean Absolute Error (MAE), Root Mean squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) are popular and widely used criteria for this purpose. Equations (15)-(17) present the computational formulas of these measures of accuracy.

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} |y_i - \hat{y}_i| \ldots\ldots\ldots\ldots\ldots (15)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} (y_t - \hat{y}_t)^2} \ldots\ldots\ldots\ldots\ldots (16)$$

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} |(y_t - \hat{y}_t) \,/\, y_t| \times 100\,\% \ldots\ldots (17)$$

Mainly, the study uses the above three criteria for basic model evaluation. The equation (18) illustrates the log likelihood function for structural time series models, and it is used to derive the log likelihood. Akaike's information criterion (AIC), bias corrected AIC (AICc) and Bayesian Information Criterion (BIC) were used particularly to evaluate the structural equation models.

$$l(\theta) = -\frac{n}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{n}\left[\log(F_t) + \frac{V_t^2}{F_t}\right] \ldots\ldots\ldots. (18)$$

Where, n is the number of observations, θ represents the vector of parameters to be estimated, V_t is the prediction error at time t, F_t is the prediction error variance at time t. AIC, BIC and corrected AIC are presented in equations (19) – (21).

$$AIC = -2ln(L) + 2k \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (19)$$

$$BIC = -2ln(L) + kln(n) \ldots\ldots\ldots\ldots\ldots\ldots (20)$$

$$AICc = AIC + \frac{2k(k+1)}{n-k-1} \ldots\ldots\ldots\ldots\ldots. (21)$$

RESULTS AND DISCUSSION

Forecasting future GDP growth rates is the primary objective of this study. These forecasts enable policymakers and government authorities to make better judgments about the dynamic nature of the future economy. Current study utilizes different versions of *Harvey-type structural decomposition*. The time series variable selected for the investigation is the quarterly GDP

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growth rates of Sri Lanka. Figure 1 provides visual illustration of the data.

Figure 1. Time Series Plot of Quarterly GDP Growth Rates: 2000 -2023
Note. The content of this figure generated based on the sample data.

According to Figure 1, there are internal and external disruptions on the trajectory of the GDP growth rates. These shocks generated uneven oscillations in GDP growth within the sample period. Therefore, it is hard to precisely predict the future of GDP behavior with these ups and downs. The lowest growth rate of GDP (-17.1%) was reported in 2020 due to the adverse effect of the global pandemic, while the highest growth rate of 13.2 % was reported in the second quarter of the year 2021. This positive recovery of the economy is due to tailoring off the pandemic and contracting several economic activities.

Forecasting is challenging due to the unusual behaviour of the data-generating process within the sample period of 23 years. The trend is one of the significant components of the Harvey-type models. Figure 1 illustrates uneven behavior of the long-term movements, including slow upward trend during 2000 to 2009, sharp positive trend between 2009 and 2012, a downward trend during 2013 and 2019, and a disrupted trend with outliers between 2020 and 2022. The behaviour of trend components clearly suggests using a decomposition method and Harvey-type may be mostly appropriate since the speed of variation of trend is changing during the period.

The first step of the analysis is to observe the data characteristics. Descriptive statistics provides

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significant information on the inherited characteristics of data, and the relevant information is given in Table 1. A variation in growth around the mean of 3.9 % implies that the economy has been able to handle external shocks or internal instabilities to a reasonable extent. The economy is slowly growing over the time horizon, though there are many disturbances in its growth trajectory. The coefficient of variation suggests that the standard deviation is about 1.268 times the average GDP growth rate, showing considerable variation in GDP growth rates within the sample period.

Table 1. Descriptive Statistics of Quarterly GDP Growth Rates: 2000-2023

	GDP
Mode	6.200
Median	5.500
Mean	3.901
Std. Deviation	4.947
Coefficient of variation	1.268
Skewness	-1.859
Std. Error of Skewness	0.246
Z of Skewness	-7.557
Kurtosis	4.446
Std. Error of Kurtosis	0.488
Z of Kurtosis	9.111
Minimum	-17.100
Maximum	13.200

Note. The content of the table generated on sample data

Seasonality is also one of the main components of STM and thus detecting the seasonal dynamic `is significant. Combination of both the graphical and statistical methods and use multiple techniques in detecting seasonality can provide a better impression of the seasonal behavior of GDP ((Makridakis et al., 1998; Cleveland et al., 1990; Hyndman & Athanasopoulos, 2021). Though there are several graphical techniques to detect seasonality, the seasonal sub-series plots are employed in this investigation because it illustrates within and between seasonal variations.

Figure 2 illustrates the seasonal sub-series plot of GDP growth rates from 2000 to 2023. It does not illustrate significant seasonal variations across quarters while showing significant fluctuations within quarters. Therefore, seasonality is altering across years rather than quarters. Overall, the subseries plot does not clearly illustrate the existence of seasonality heightening the unpredictability of the behaviour of GDP.

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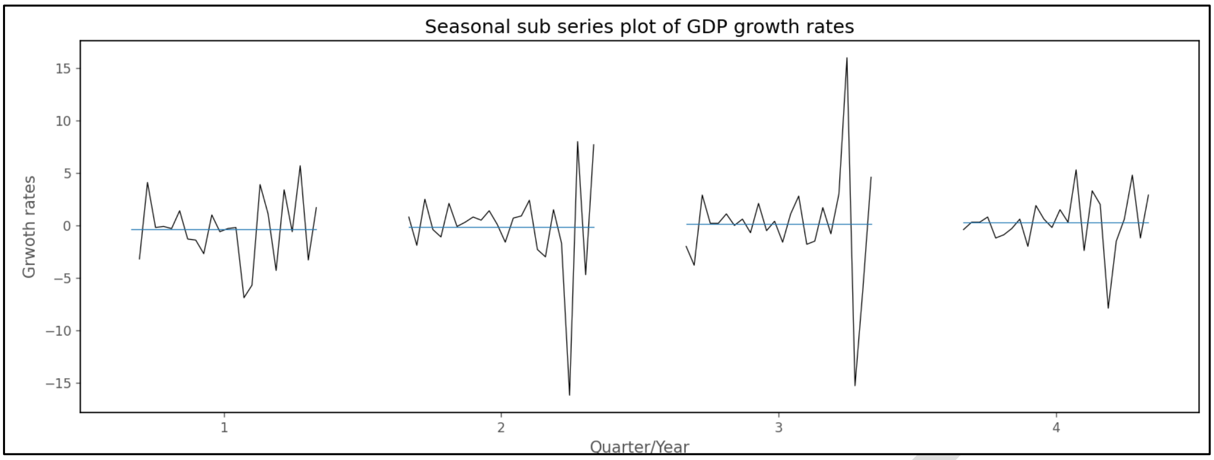

Figure 2. Seasonal Sub Series Plot of Quarterly GDP Growth Rates: 2000-2023
Note. The content of the figure generated using sample data.

Dummy variable regression enables the evaluation of seasonality and its statistical significance. Table 2 presents the results of dummy variable regression conducted for detecting seasonality in GDP growth rates.

The dummy variable regression analysis indicates that none of the quarterly dummies are statistically significant, with all *p*-values well above standard levels. The overall explanatory power of the model is extremely low, as reflected by an R-squared value of just 0.16 suggesting the model performs worse than a simple mean prediction. Additionally, the Durbin-Watson statistic of 2.49 suggests no strong evidence of autocorrelation. Overall, the findings imply that seasonal effects, as captured by the included dummies, do not meaningfully explain variation in the dependent variable. Therefore, no prominent seasonal effects of quarterly GDP. Though there are no significant seasonal fluctuations, it suggests not to use seasonal component in decomposition models.

Table 2. Estimates of the seasonal component

	Coefficient	**Std. error**	**t-ratio**	***p*-value**
Constant	7.16326	1.24291	5.763	1.11e-07 ***
d2	−0.0674484	1.34025	−0.0503	0.9600
d3	0.119270	1.34058	0.08897	0.9293
d4	0.489322	1.34112	0.3649	0.7161
time	−0.0700516	0.01711	−4.0940	9.18e-05 ***

Mean dependent var	3.901042	S.D. dependent var	4.946695
SSE 1961.211	S.E. of regression	4.642388	
R-squared	0.156334	Adjusted *R*-squared	0.119250
F (4, 91)	4.215654	*p*-value(F)	0.003548
Log-likelihood	−281.0326	Akaike criterion	572.0652
Schwarz criterion	584.88700	Hannan-Quinn	577.2480
rho	0.634847	Durbin-Watson	2.491936

Note. The content of the table was computed using sample data

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Different variations of the equation (12) as given under materials and methods section were estimated and the summary of estimates are given in Table 3. The Table 3 compares for structural time series models to identify the most suitable model specification, including trend, seasonality, and intervention effects. All model specifications have been estimated amalgamating time-varying components. The results have confirmed that time-varying model with a third-order polynomial trend and a pulse intervention is the best fitting specification, resulting the lowest AIC, BIC, and RMSE values. The selected model captures dynamic trend with positive level and slope values. Although the seasonal component was statistically and insignificant, short-term seasonal effects have been incorporated to accommodate the short-term seasonal fluctuations. The effect of world pandemic is represented with a pulse intervention component which effectively investigate a sudden change in the series. The proposed model can strongly track the underlying data structure as shown in model's low irregular variance and improved in-sample accuracy measures. Overall, findings emphasise that inclusion of flexible trend model and intervention effects improves the model performance, ensuring the selected model specification is the best fitting for understanding complex and dynamics behaviour in time series with external shocks or structural breaks.

Table 3. Summary of the estimates of variations of model given in equation (19)

Variance of disturbances				
Model type	Level variance	Slope variance	Seasonal variance	Irregular variance
Local level	3.584	-	-	5.9220
Basic structural	4.059	0.0000		5.5780
Time varying + intervention	3.330	-	0.0000	6.4040
Time varying model with 3^{rd} order trend + intervention	15.6678	0.0016	0.0016	0.0157
	Seasonal short properties[1]			
	Period_1	Period_2	Period_3	Period_4
Time varying model with 3^{rd} order trend + intervention	-0.2508 (-0.6690)	0.3410 (0.9007)	-0.2104 (-0.5658)	0.1201 (0.3205)
Seasonal chi-Square				1.688 (0.6397)
State vector at period 2023-10-01				
Level	3.9514	1.0949	5.0516e-04	
Model fitting accuracy measures	Local level	Basic structural	Time varying + intervention	Time varying model with 3^{rd} order trend + intervention
Log likelihood	-239.360	-239.888	-239.206	-224.302
Akaike Information Criterion (AIC)	484.719	487.776	490.412	443.214

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Bias corrected AIC	484.998	488.247	491.424	441.742
Bayesian Information Criterion (BIC)	492.219	497.775	505.411	432.832
In-sample MSE	12.660	13.241	14.196	10.142
In-sample RMSE	3.558	3.639	3.768	2.981
In-sample MAE	2.272	2.298	2.419	1.971
In-sample MAPE	129.697	108.139	153.333	102.543
Effective sample size	90	90	90	90

1. t-ratios are given in parentheses

The next step of this investigation is to generate forecasts based on the best fitting model. However, for a comparative analysis, all specifications were employed in geniting forecast, enabling the validity of the best suited model specification. Table 4 presents a summary of the forecasting endeavour.

Table 4. Forecast Values of the GDP Growth of Sri Lanka Using Harvey-Type Structural Time Series Decomposition Models

Time	Harvey-type structural decomposition specification			
	Local level model	Basic structural model	Time varying model with intervention	Time varying model with 3rd order trend + intervention
2024-Q1	3.295	2.944	3.670	5.279
2024-Q2	3.295	2.807	4.231	4.573
2024-Q3	3.295	2.923	3.649	5.392
2024-Q4	3.295	3.223	3.949	5.509
2025-Q1	3.295	2.789	3.548	4.063
2025-Q2	3.295	2.651	4.109	5.091
ω_1			-16.77 (0.0000)	-16.09 (0.0000)
ω_2				-11.66 (0.0000)
RMSE	3.773	4.041	3.727	3.584
MAE	2.421	2.605	2.410	2.373
MAPE	133.905	125.182	120.058	113.052
LL	-260.980	-261.534	-240.903	-233.313
AIC	527.959	537.067	497.806	482.625
AICc	528.220	538.340	499.461	484.280
BIC	535.652	555.018	518.321	503.140

Note. The content of the table generated from sampled data. *P* values are in parentheses.

Table 4 comparatively evaluates four Harvey-type structural decomposition models—Local Level, Basic Structural, Time-Varying with Intervention, and Time-Varying with 3rd Order Trend plus Intervention. This comparison enables comprehensive analysis into the models' forecasting accuracy and structural flexibility. The Local Level model reflects its failure to adapt to temporal dynamics remaining forecasts as a constant at 3.295 across all quarters. The Basic Structural model illustrates modest variability of forecasts changing between 2.651 and 3.223. However, it reveals that the model specification is less suitable for capturing rapid economic shifts. In contrast, the Time-Varying models ensure significant improvements. The Time-Varying model with Intervention generates forecasts between 3.548 and 4.231, while the Time-Varying model with 3rd order Trend and Intervention generates comparatively higher values, ranging from 4.063 to 5.509, demonstrating a greater flexibility in accommodating highly volatile changes.

Model performance measures further strengthen these findings. The Time-Varying model with 3rd order Trend and Intervention achieved the lowest RMSE (3.584), MAE (2.373), and MAPE (113.052), along with the highest log-likelihood (−233.313) and the most favourable AIC, AICc, and BIC scores. The statistically significant intervention effects (ω_1 and ω_2) components at the 1% level underlines the significance of inclusion of intervention events into the model specifications.

Comparison of forecasts values under different specifications with actual quarterly GDP growth rates in 2024 (Q1: 5.3%, Q2: 4.7%, Q3: 5.5%, Q4: 5.4%) reveals that the Time-Varying model with 3rd order Trend and Intervention reliably generates closer forecasts to the observed growth rates. Specifically, this model's forecasts (5.279%, 4.573%, 5.392%, and 5.509% respectively) were extremely associated with actual figures, outperforming the more rigid Local Level and Basic Structural models, whose underestimations were significant. Overall, the Time-Varying model with 3rd order Trend and Intervention emerges as the most robust specification, offering both superior in-sample fit and higher forecasting reliability for dynamic economic conditions.

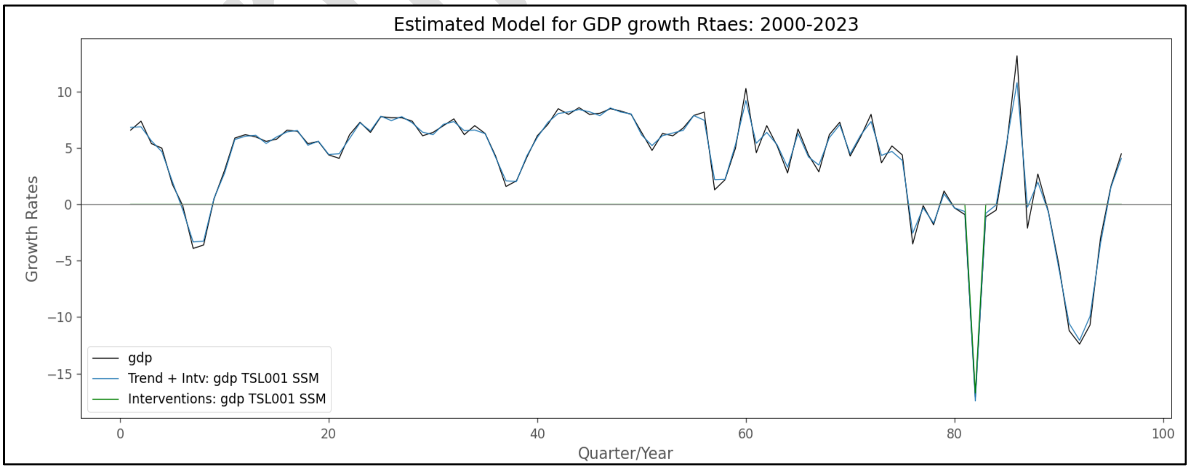

Figure 3. Illustration of GDP and Fitted STM Model plus Intervention for Original Data
Note. The content of the figure generated using sample data.

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Figure 3 illustrates the goodness of fit of the Time-Varying Model with the 3rd order Trend and Intervention model. The Figure plots the true GDP growth rates, model fits, and an intervention component. The intervention components capture the significant effect of the global financial crisis around 2008 and the COVID-19 pandemic in 2020. These interventions resulted in a sharp deviation of GDP growth from its trend. Therefore, the intervention analysis introduced into the model to effectively captures these anomalies when predicting the GDP growth rates. The ability to incorporate the intervention components is one of the advantages of the structural time series models over the other decomposition models.

The estimated model for Sri Lanka's quarterly GDP growth rates from 2000 to 2023 shows strong adequacy. The actual growth rates closely align with the predictions of the model Time-Varying model with 3rd order Trend and Intervention indicating a good fit. The model effectively separates regular economic patterns from one-off shocks, as seen in the clear intervention effects during extreme events like COVID-19. Small deviations between actual and predicted values are minimal, during highly volatile periods. Overall, the model reliably captures both long-term trends and short-term disruptions, supporting its suitability for explaining and forecasting GDP growth rates. Figure 4 presents the visual impression of the forecasting of GDP growth rates with structural time series decomposition.

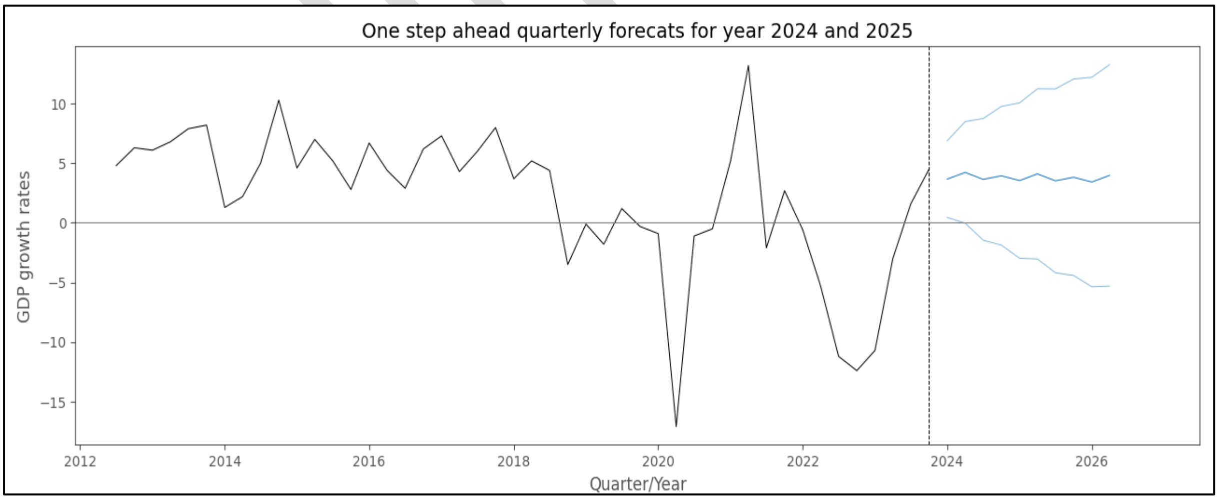

Figure 4. Fitted and Forecasts of GDP Growth Rates Using Fitted Harvey-Type STM Model
Note. The content of the figure generated using sample data.

The confidence intervals are not visible for the training sample, indicating the high accuracy of the estimated model, because e they are overlapping. The forecasting horizon extends to the second quarter of the year 2025. It shows oscillations, and these fluctuations are common in forecasting the natural behaviour of a time series. Since the confidence intervals of forecasts widen in the future, uncertainty increases when the forecasting horizon extends. It is a typical characteristic in forecasting for the long term with time series models. Therefore, the estimated model should not be used for long-term forecasting. It is suitable for forecasting short-term movements. Consequently, it is advisable to revise the model when new observations are available by adding the actuals into the current time series.

CONCLUSIONS AND POLICY RECOMMENDATIONS

This study employed a variety of Harvey-type decomposition time series forecasting methods to predict Sri Lanka's GDP growth rates in the future using the sample period from the first quarter of 2000 to the fourth quarter of 2023. This empirical investigation included different versions of Harvey-type decomposition time series forecasting methods, including Local Level, Basic Structural, Time-Varying with Intervention, and Time-Varying with 3rd Order Trend plus Intervention specifications. This comprehensive analysis provides valuable insights into GDP growth and the behaviour of the growth rates in Sri Lanka. Among these models, the Harvey-type Time-Varying with 3rd Order Trend plus Intervention specification shows improved performance. The improved performance of the model was determined based on lower AIC, AICc, and BIC values and better-fit measures of accuracy such as RMSE, MAE, and MAPE. The intervention analysis in the structural time series models allowed for a more accurate understanding of the impact of significant disturbance on economic growth trajectory over time. The application of current models and its performance has been justified in Andrews (1994), Dreuw, (2023), Guillén & Rodríguez, (2014) and Harvey & Peters (1990).

According to the findings of this study, the behaviour of GDP growth is dynamic, involving trends, time-varying seasonal patterns, and the presence of intervention effects. Consequently, this study recommends that policymakers strengthen real-time economic monitoring frameworks using state-space modelling approaches, which enable early detection of structural changes and financial shocks. Flexible fiscal and monetary policies should permit rapid adjustments to unexpected fluctuations in economic activities. It also recommends seasonally adjusted fiscal planning, ensuring targeted public investment in instantaneous economic activities during low-growth quarters. Trend instability stimulates long-term investments, ensuring financial resilience remarkably through productivity-driven sectors. Finally, the predictive power of the decomposition time series models proposes to formally integrate forecast-

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based scenarios into national budgeting and policy formulation processes. Such suggestions will enhance the ability to adapt promptly and sustainably to changing conditions.

The future direction of this research enables the exploration of several new avenues for further enhancing the understanding of the complexities of the GDP growth rates. One of the aspects of future research is incorporating the explanatory variable(s) into structural models. This approach would provide a more comprehensive analysis by capturing external and internal shocks in the economic growth trajectory. Another potential area is to use machine learning techniques, new developments in forecasting, will enhance the model's predictability and forecasting accuracy under highly volatile economic conditions.

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