

# Forecasting - Final Assignment

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## 2 Executive Summary

This report presents the findings of a comprehensive analysis and evaluation of various forecasting methods applied to time series data from the M3 competition data set. The project aimed to explore the efficacy of different statistical models in accurately predicting future values of quarterly time series data, both through manual forecasting for individual series and batch forecasting for a range of series.

Through meticulous analysis and comparison, it became evident that the regression model stood out as the most accurate method in manual forecasting, surpassing both exponential smoothing with the Holt-Winters method and ARIMA models in terms of accuracy metrics. Moreover, during batch forecasting, evaluations of automatic ARIMA, automatic ETS, and TBATS models against Theta and Damped Exponential Smoothing models failed to surpass the latter in performance.

## 3 Introduction

Forecasting is a vital tool for decision-making across diverse domains. It enables organisations to anticipate future trends, allocate resources efficiently, and mitigate risks effectively. In practice, accurate forecasting is indispensable for strategic planning, inventory management, and market analysis.

This report delves into the practical aspects of forecasting by evaluating different statistical models applied to time series data. Time series forecasting, encompassing manual and batch approaches, is instrumental for businesses and organisations to optimise operations and capitalise on emerging opportunities.

The report focuses on analysing and forecasting quarterly time series data from the M3 competition data set, spanning various sectors such as finance, economics, and demographics. Each time series represents a historical record of a specific variable, such as sales numbers, stock prices, or production levels, recorded at regular intervals—yearly, quarterly, or monthly. By leveraging manual forecasting techniques for individual series and batch fore-



casting methods for multiple series simultaneously, this study aims to provide insights into the effectiveness of different forecasting methodologies.

According to Koning, Franses, Hibon and Stekler (2005), four main conclusions of the M3 competition were derived from descriptive statistics analysis with no formal statistical testing. First, the complexity of forecasting methods does not always correlate with forecast accuracy; simpler methods can be equally effective. Second, the performance rankings of different methods vary depending on the accuracy measure employed. Third, combining various forecasting methods tends to yield better results than using individual methods alone, demonstrating superior performance overall. Lastly, the effectiveness of forecasting methods is influenced by the length of the forecasting horizon.

## 4 Manual Modelling

### 4.1 Exploratory analysis

In this section, we focus on series ID 1394 from the M3 forecasting competition, which tracks quarterly demographic data, specifically unemployment in Canada. This time series is valuable for analysts and researchers studying labour market trends in Canada and could aid in developing forecasting models to predict future unemployment based on historical patterns. We assume the data has been adjusted to represent per capita data. A summary of series 1394 is provided below (R code 8.1).

Table 1: M3 competition series ID 1394

```
$st
```

```
[1] "Q749"
```

```
$type
```

```
[1] "DEMOGRAPHIC"
```

\$period

[1] "QUARTERLY"

\$description

[1] "UNEMPLOYMENT- CANADA"

\$sn

[1] "N1394"

\$x

	Qtr1	Qtr2	Qtr3	Qtr4
1962	5610	3730	2820	3460
1963	5460	3720	2720	3050
1964	4630	3260	2430	2660
1965	3970	2980	2100	2140
1966	3520	2580	2260	2330
1967	3920	3200	2500	2990
1968	4780	3990	3170	3330
1969	4630	4000	3150	3500
1970	5180	5290	4550	4780
1971	6640	5840	4680	4930
1972	6450	5710	5020	5300
1973	6500	5220	4380	4700

\$xx

	Qtr1	Qtr2	Qtr3	Qtr4
1974	6240	5200	4480	5070
1975	8320	7380	6210	6380

\$h

[1] 8

\$n

[1] 48

Within the context of the M3 competition data set, ‘x’ serves as the historical (a.k.a. training) time series data from 1962 to 1973, which is used to develop and calibrate forecasting models, while ‘xx’ acts as the future (a.k.a. test) data set from 1974 to 1975, which is used to evaluate the performance and accuracy of the models’ predictions.

Producing a time series plot of the historical data (Figure 1) and its summary will help gain insights into the data’s characteristics (R code 8.2).



Figure 1: Quarterly unemployment in Canada in 1962-1973

Table 2: Summary of the quarterly unemployment in Canada in 1962–1973

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
2100	3035	3945	4037	4952	6640

The series exhibits a downward trend before 1966, followed by a clear upward trend starting in 1966, indicating an increase in the unemployed since then. A strong seasonal pattern is evident in Figure 2, with peaks and troughs corresponding to particular times of the year (Q1 and Q3, respectively) (Figure 3), suggesting likely annual seasonality influenced by various factors related to economic activity, societal habits, and institutional schedules (R code 8.3).

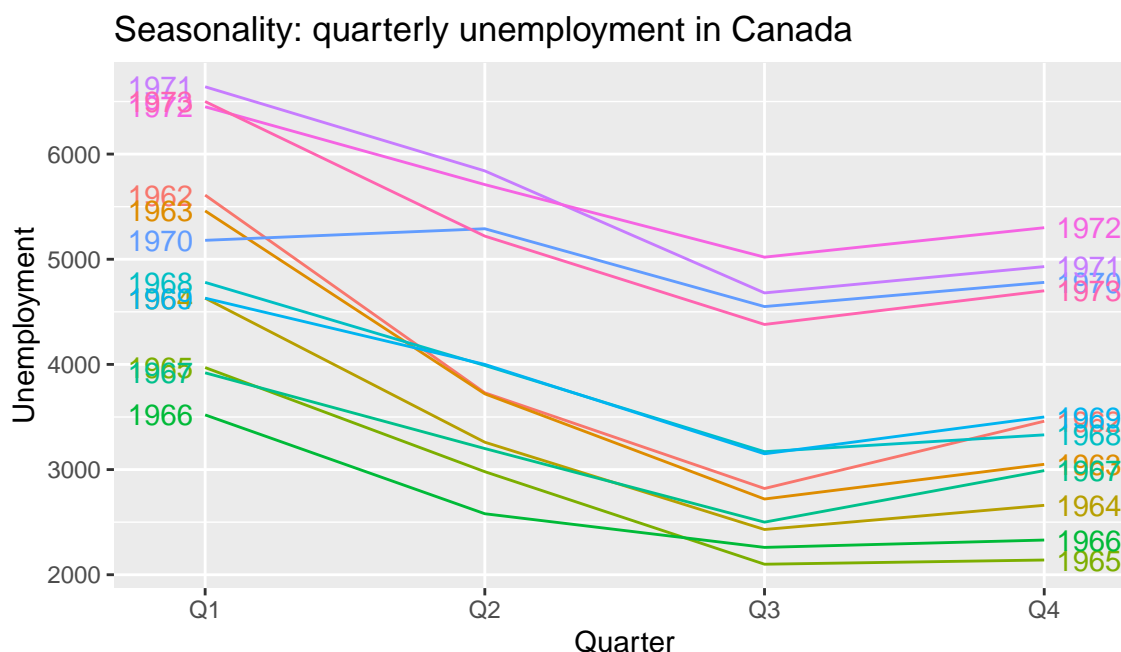


Figure 2: Seasonality plot of the quarterly unemployment in Canada in 1962-1973

The lagged scatter plots of the quarterly Canadian unemployment (Figure 4) reveal a strongly positive relationship at lag 4, reflecting the strong seasonality in the data (R code 8.4).

As the data are both trended and seasonal, we observe the slow decay in autocorrelation associated with the trend component alongside more significant spikes at lags matching the seasonal period in Figure 5 (R code 8.5).

As the data exhibits both trend and seasonality, decomposition can be a valuable insight by separating the time series into trend, seasonality, and residual components. Upon decomposing the time series, the multiplicative type of decomposition effectively subtracts the seasonal and trend-cycle components from the training data in Figure 6 (R code 8.6).

However, discerning longer-term cyclical fluctuations in Canada's unemployment due to

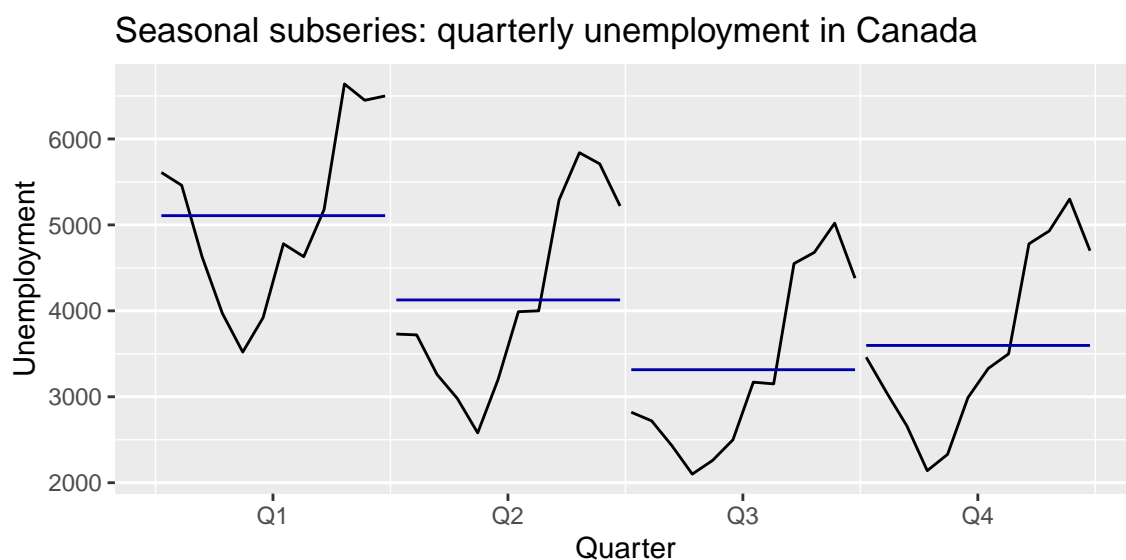


Figure 3: Seasonal subseries plot of the quarterly unemployment in Canada in 1962-1973

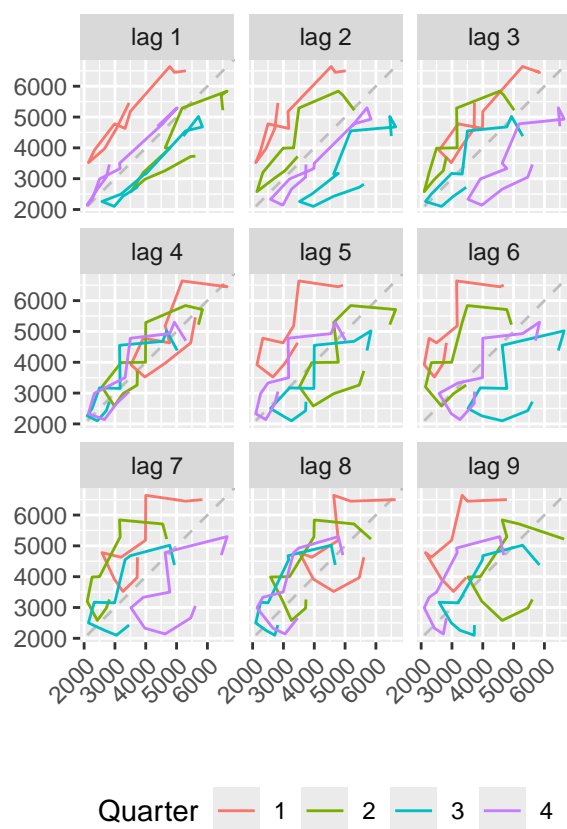


Figure 4: Lagged scatter plots of the quarterly unemployment in Canada in 1962-1973



Figure 5: Autocorrelation Function (ACF) plot of the quarterly unemployment in Canada in 1962-1973

broader economic conditions within the limited time frame of the plot (spanning from 1962 to 1973) may be challenging. Extended data covering a more prolonged period would be necessary to reliably identify and confirm these broader economic trends and their impact on unemployment.

Based on the above, any forecasts of this series would need to capture the trend and seasonal patterns.

Detecting outliers in time series data in Figure 7 is critical as they can significantly impact analysis and forecasts (R code 8.7).

By generating boxplots for each quarter to detect outliers within each period, we conclude there are no outliers that could affect forecasting.

## 4.2 Regression modelling, analysis and forecasting

Considering the presence of changing trends and seasonality in the historical data, a regression model with trend and seasonal components as predictors seems appropriate. However,

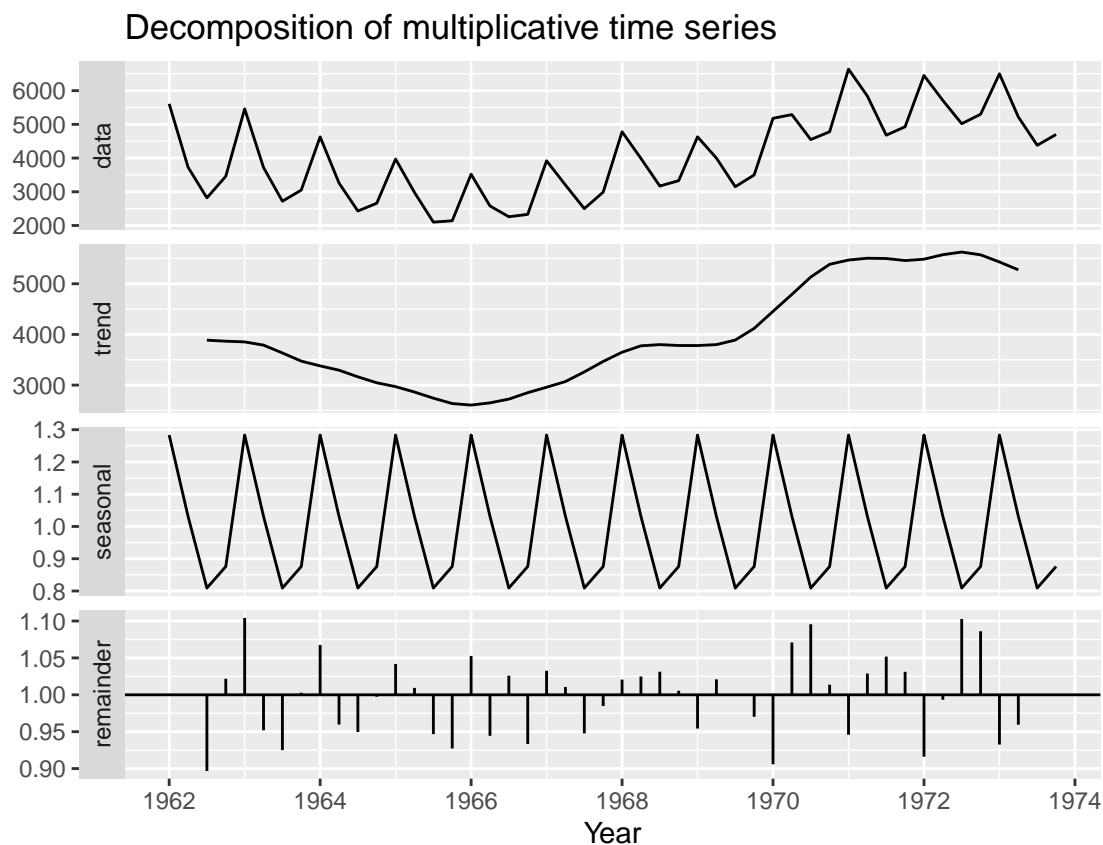


Figure 6: Decomposed quarterly unemployment in Canada in 1962-1973



Figure 7: Distribution of unemployment in Canada in 1962-1973 per quarter

to adjust the model to capture the parabolic shape of the time series, we add quadratic and cubic trend components to capture any curvature or parabolic shape in the training time series data. We will fit a polynomial regression model using the `tslm()` function in R, specifically designed for time series data (R code 8.8).

Table 3: Regression model summary

Call:

```
tslm(formula = training_data ~ trend + I(trend^2) + I(trend^3) +
      season)
```

Residuals:

Min	1Q	Median	3Q	Max
-751.41	-261.72	48.11	231.77	732.82

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	6.113e+03	2.407e+02	25.394	< 2e-16 ***
trend	-3.551e+02	4.045e+01	-8.779	5.80e-11 ***
I(trend^2)	1.651e+01	1.908e+00	8.653	8.57e-11 ***
I(trend^3)	-1.863e-01	2.561e-02	-7.274	6.78e-09 ***
season2	-9.863e+02	1.500e+02	-6.576	6.56e-08 ***
season3	-1.810e+03	1.505e+02	-12.026	5.00e-15 ***
season4	-1.544e+03	1.513e+02	-10.204	8.08e-13 ***

---

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 366.9 on 41 degrees of freedom

Multiple R-squared: 0.9245, Adjusted R-squared: 0.9135

F-statistic: 83.68 on 6 and 41 DF, p-value: < 2.2e-16



The model demonstrates a good fit to the training data in Figure 8 (R code 8.9), explaining approximately 92.45% of the variance, and is statistically significant based on the F-statistic. The coefficients for the trend terms and seasonal components are statistically significant at conventional levels, indicating their significant effects on the response variable. Specifically, there is an average upward trend of 54.20 unemployed units per quarter. On average, the second quarter experienced unemployment at approximately 986.3 units lower than the first quarter, the third quarter was 1810 units lower, and the fourth quarter was 1544 units lower.

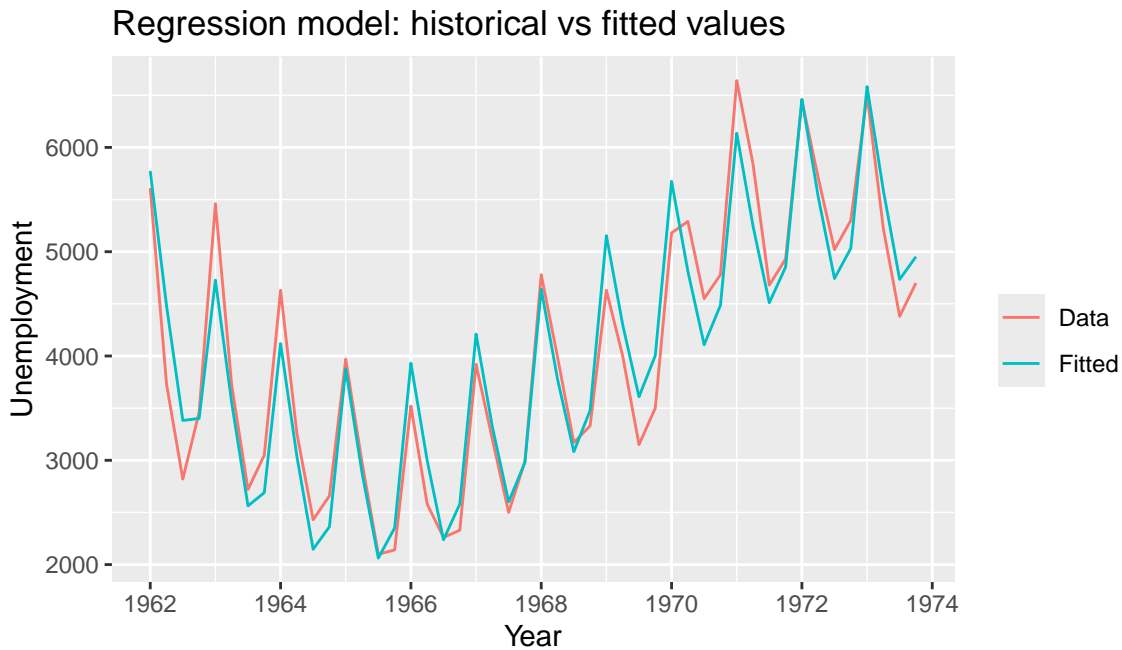


Figure 8: Regression model: quarterly unemployment in Canada in 1962-1973 vs. fitted values

The residual standard error is relatively low (366.9), suggesting that the model provides a satisfactory fit to the data. Based on the Shapiro-Wilk test (R code 8.10), there is no sufficient evidence to conclude that the residuals significantly depart from a normal distribution, indicating that the assumption of normality may be reasonable.

Table 4: Shapiro-Wilk test of the regression model’s training residuals

Shapiro-Wilk normality test

```
data: regression_model$residuals
```

```
W = 0.98485, p-value = 0.7853
```

The residuals appear to be normally distributed, and there are no apparent patterns in the residual plots in Figure 9 (R code 8.11).

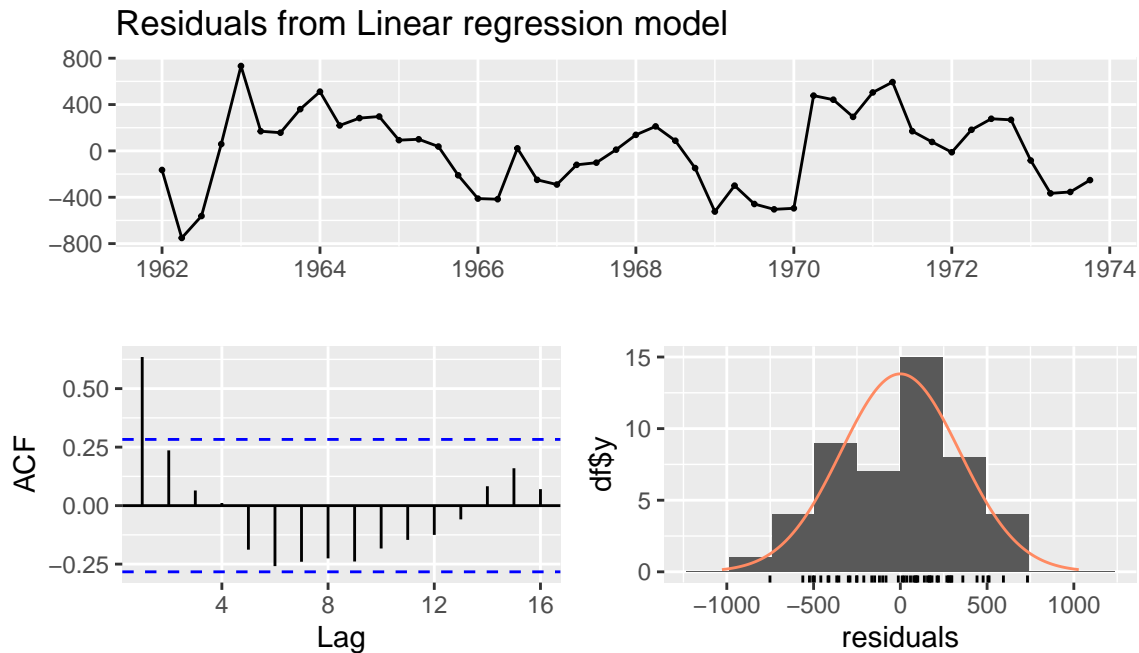


Figure 9: Training residuals from the regression model

Breusch-Godfrey test for serial correlation of order up to 10

```
data: Residuals from Linear regression model
```

```
LM test = 27.31, df = 10, p-value = 0.002326
```

However, the Breusch-Godfrey test, indicating evidence of serial correlation in the residuals from the linear regression model, and the residuals' Autocorrelation Function plot reveals significant autocorrelation at lag 1, suggesting a violation of the assumption of independence.

Subsequently, the Ljung-Box test confirms significant autocorrelation in the training residuals at lag 1, indicating that a time series model explicitly addressing autocorrelation, such as an ARIMA model, may offer a better fit (R code 8.12).

Table 5: Box-Ljung test of the regression model's training residuals

#### Box-Ljung test

```
data: regression_model$residuals
X-squared = 20.593, df = 1, p-value = 5.68e-06
```

When evaluating the regression model's forecasting performance on future data displayed as a dashed black line in Figure 10 (R code 8.13), we notice that it predicts unemployment reasonably well for the first four quarters, with the future data lying within the 80% confidence interval. However, future unemployment sharply increased during the last four quarters, contrary to the regression model's forecast, which exhibits a clear downward trend. This discrepancy suggests that the model may not capture specific patterns or information present in the data.

The Ljung-Box test suggests that there may be some remaining patterns or information in the out-of-sample residuals that the model has not captured, as the p-value (0.07898) is greater than the conventional significance level of 0.05 (R code 8.14).

#### Ljung-Box test

```
data: Residuals
Q* = 6.7876, df = 3, p-value = 0.07898
```

```
Model df: 0.    Total lags used: 3
```

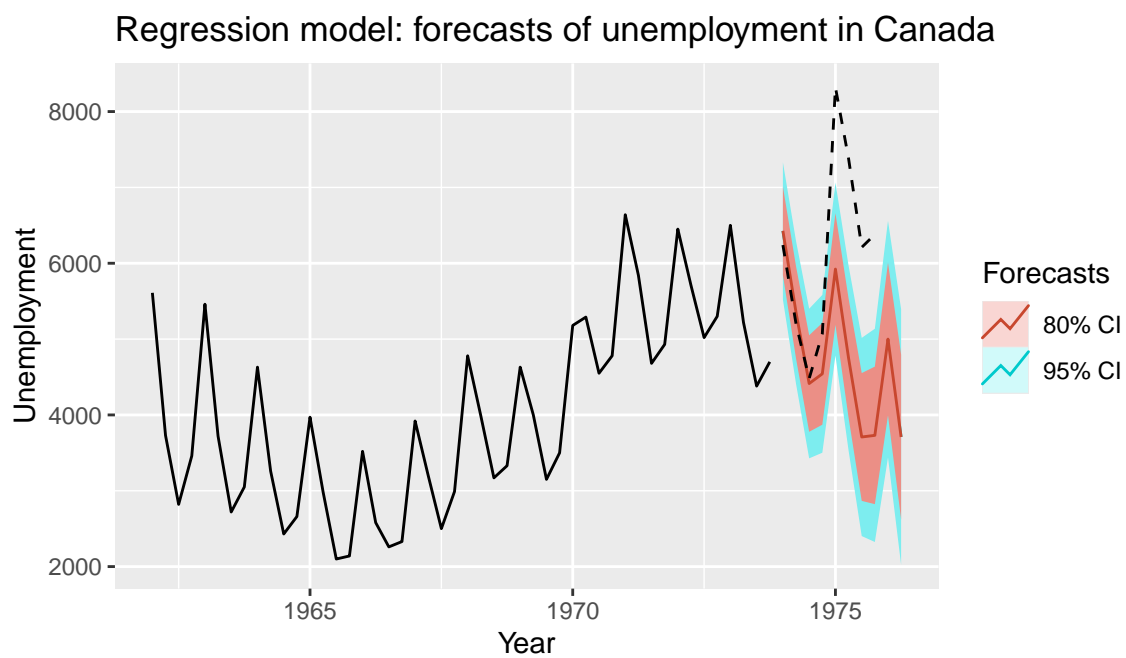


Figure 10: Regression model's eight-quarter forecast of unemployment in Canada

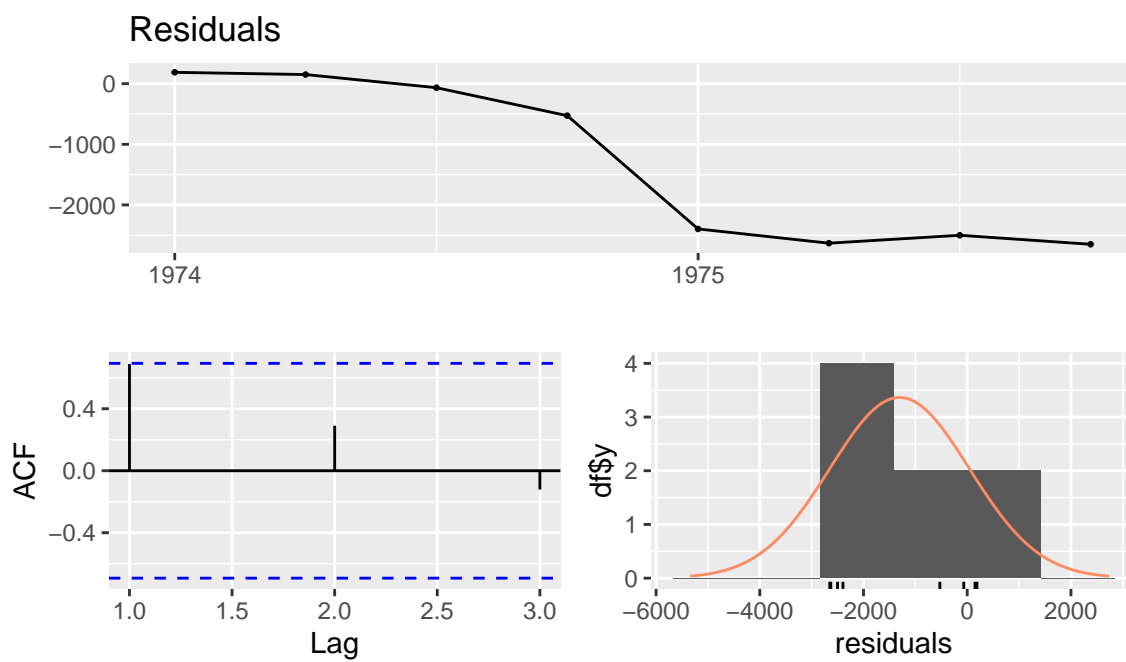


Figure 11: Regression model: out-of-sample residuals

We can use various evaluation metrics, such as MAE, RMSE, and MAPE, to evaluate the accuracy of the regression model's forecasts of future data (R code 8.15).

Table 6: Error measures evaluating the regression model's out-of-sample accuracy

Mean Absolute Error (MAE)	1388.74895
Root Mean Squared Error (RMSE)	1812.55196
Mean Absolute Percentage Error (MAPE)	20.50523
Forecast Bias	-1304.32674

An RMSE of 1812.552 indicates that, on average, the forecasted values deviate from the actual future values by approximately 1812.552 units. The MAPE suggests that, on average, the forecasts deviate from the actual future values by approximately 20.50523%. The bias indicates that, on average, the forecasts tend to underestimate the actual values by approximately 1304.327 units.

Overall, the forecasting performance of this model seems to have moderate accuracy. The MAE, RMSE, and MAPE values suggest that the forecasts have a reasonable level of accuracy, although there is room for improvement. Additionally, the negative bias indicates a tendency for the forecasts to be consistently lower than the actual values.

Notably, the significant jump in unemployment observed in 1975, the highest value throughout the observation period, indicates an extraordinary event that the model could not consider. This highlights the challenge of forecasting, which assumes that future patterns and behaviours will resemble those observed in the past.

### 4.3 Exponential smoothing modelling, analysis and forecasting

To manually fit a model from the exponential smoothing family, tailored for time series data exhibiting trend and seasonality, the Holt-Winters method is a suitable choice. This method extends simple exponential smoothing to accommodate data with both trend and

seasonality. We will fit the Holt-Winters model incorporating multiplicative error, additive trend with damping, and multiplicative seasonality components (ETS(M,Ad,M)) (R code 8.16).

Table 7: Exponential Smoothing model with the Holt-Winters method summary

ETS(M,Ad,M)

Call:

```
ets(y = training_data, model = "MAM", damped = TRUE)
```

Smoothing parameters:

alpha = 0.4065

beta = 0.4065

gamma = 0.5796

phi = 0.8758

Initial states:

l = 4134.9175

b = -5.4187

s = 0.881 0.7053 0.9446 1.4691

sigma: 0.0855

	AIC	AICc	BIC
	752.0501	757.9960	770.7621

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-28.89258	321.5432	244.6389	-0.1225624	5.976051	0.5334049
	ACF1					

Training set 0.3023249

A sigma value of 0.0855 suggests that the model captures a significant portion of the variability in the training data. Additionally, the relatively low values of AIC, AICc, and BIC are positive indicators of model fit.

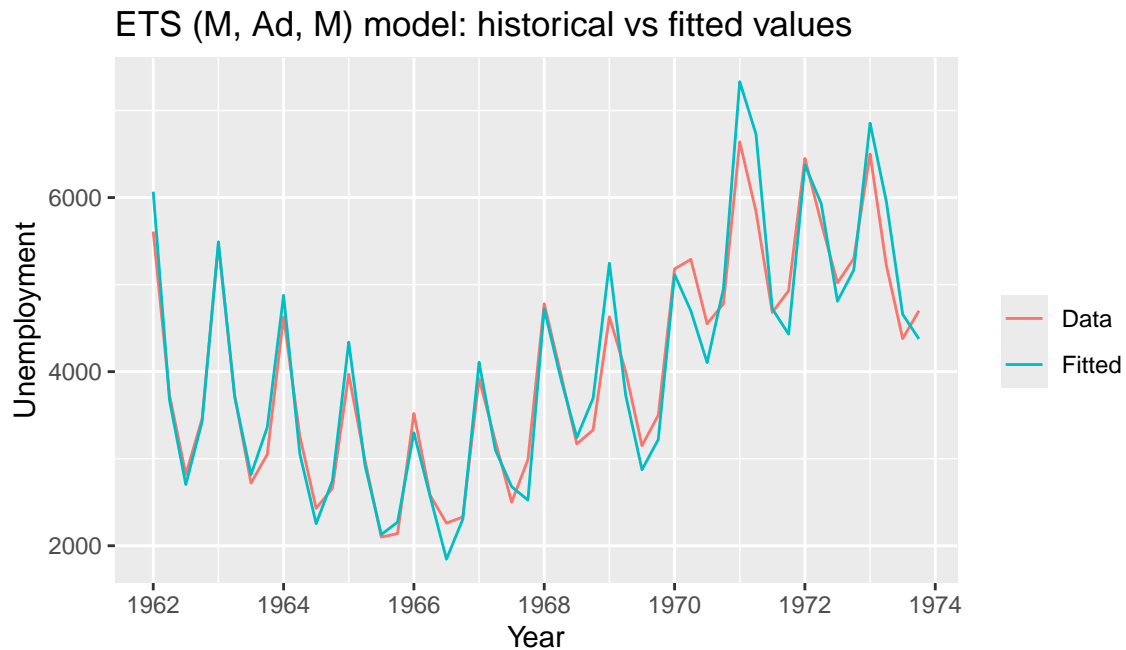


Figure 12: Exponential smoothing (ETS (M, Ad, M)) model: quarterly unemployment in Canada in 1962-1973 vs. fitted values

Upon examination of residuals (R code 8.17), they appear to be normally distributed without any discernible patterns.

Ljung-Box test

data: Residuals from ETS(M,Ad,M)

Q\* = 14.359, df = 8, p-value = 0.07287

Model df: 0. Total lags used: 8

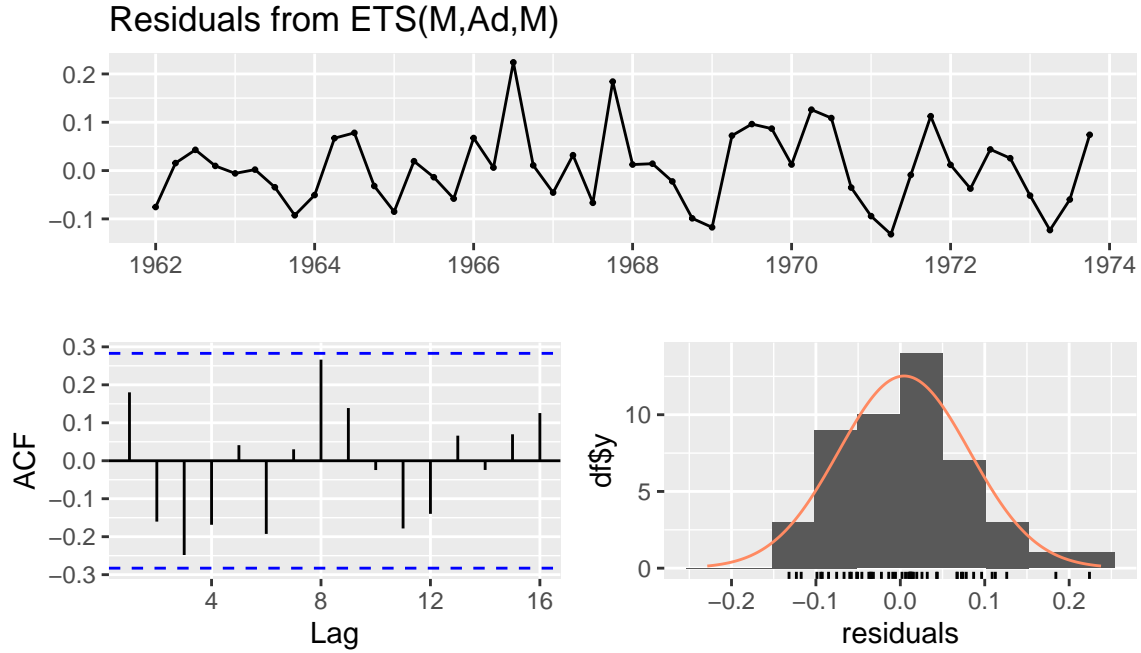


Figure 13: Exponential smoothing (ETS (M, Ad, M)) model: training residuals

It is supported by the Shapiro-Wilk test results, which do not provide sufficient evidence to reject the assumption of normality (R code 8.18).

Table 8: Shapiro-Wilk test of the exponential smoothing model's training residuals

#### Shapiro-Wilk normality test

```
data: hw_model$residuals
W = 0.97488, p-value = 0.3875
```

However, further evaluation of the model on future data is warranted to provide a comprehensive assessment.

When evaluating the forecasting accuracy of the exponential smoothing model with the Holt-Winters method against future data in Figure 14 (R code 8.19), we observe that while the future data aligns with the 95% confidence interval for the first four quarters, it surpasses the forecasted range thereafter.



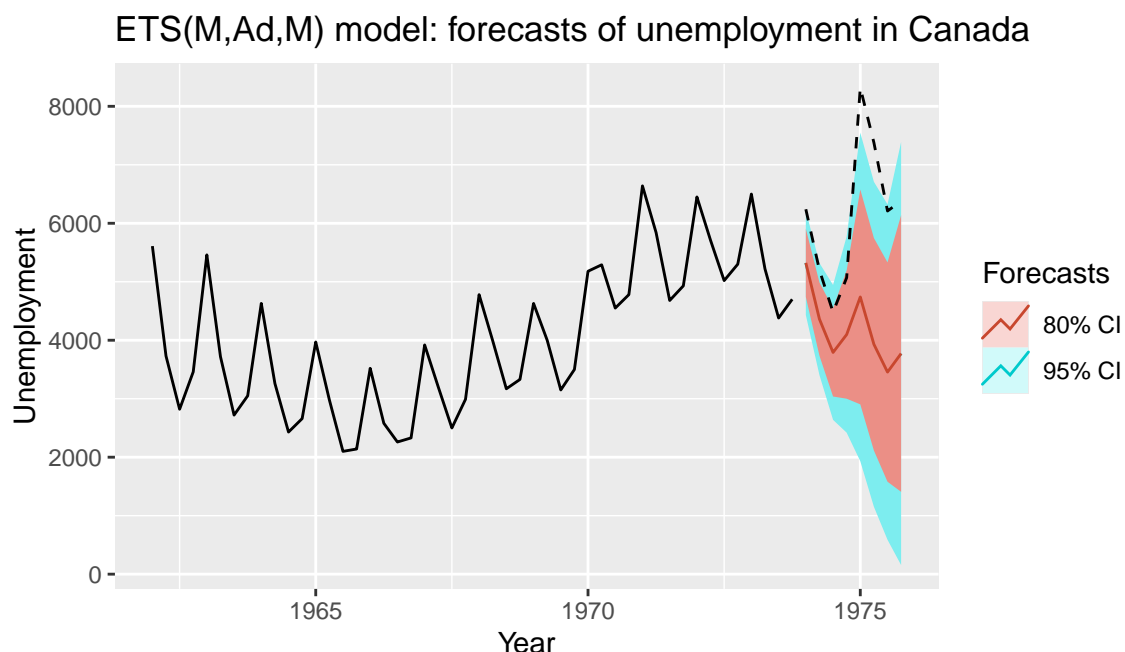


Figure 14: Exponential smoothing (ETS (M, Ad, M)) model's eight-quarter forecast of unemployment in Canada

This discrepancy makes it challenging to directly assess the model's forecasting performance solely based on this plot. Therefore, we conduct residual analysis in Figure 15 to obtain a more objective evaluation and examine various evaluation metrics such as MAE, RMSE, and MAPE (R code 8.20).

#### Ljung-Box test

data: Residuals

$Q^* = 4.8876$ ,  $df = 3$ ,  $p\text{-value} = 0.1802$

Model df: 0. Total lags used: 3

The Ljung-Box Test Statistic's p-value (0.1802) is greater than the commonly used significance level of 0.05, suggesting no significant autocorrelation in the residuals at the specified lags.

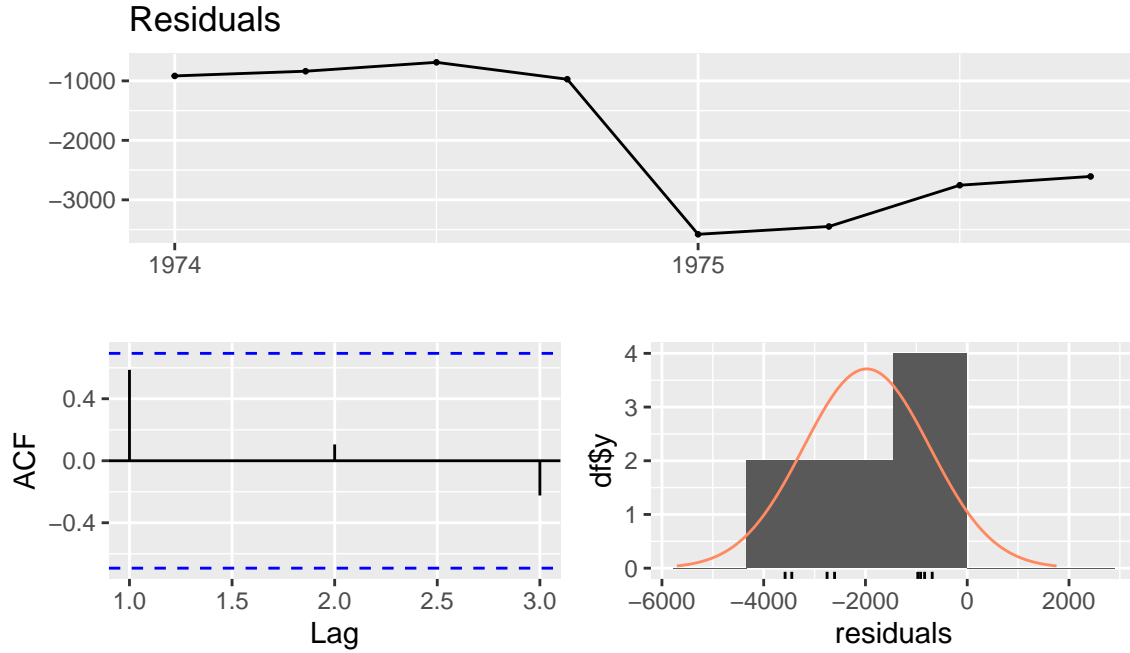


Figure 15: Exponential smoothing (ETS (M, Ad, M)) model: out-of-sample residuals

However, the model exhibits poor performance compared to the future data (R code 8.21).

Table 9: Error measures evaluating ETS(M,Ad,M) model's out-of-sample accuracy

Mean Absolute Error (MAE)	1975.5170
Root Mean Squared Error (RMSE)	2292.6355
Mean Absolute Percentage Error (MAPE)	30.0379
Forecast Bias	-1975.5170

High MAE and RMSE values indicate significant deviations from actual values on average, while a MAPE of 30.0379% suggests considerable discrepancies relative to actual values. A lower MAPE is desired for more accurate forecasts. Furthermore, the negative bias indicates a systematic underestimation of actual values.

In conclusion, the model's performance is subpar, characterised by high errors, substantial deviations from actual future values, and systematic bias. Further refinement or alternative modelling approaches may be necessary to enhance forecasting accuracy.

## 4.4 ARIMA modelling, analysis and forecasting

As established earlier in this report, the historical time series data exhibits trend and seasonality components, rendering it non-stationary. This is confirmed by the Autocorrelation Function (ACF) plot in Figure 16 (R code 8.22), which displays multiple spikes outside the confidence intervals, with a notably strong and significantly positive first lag.

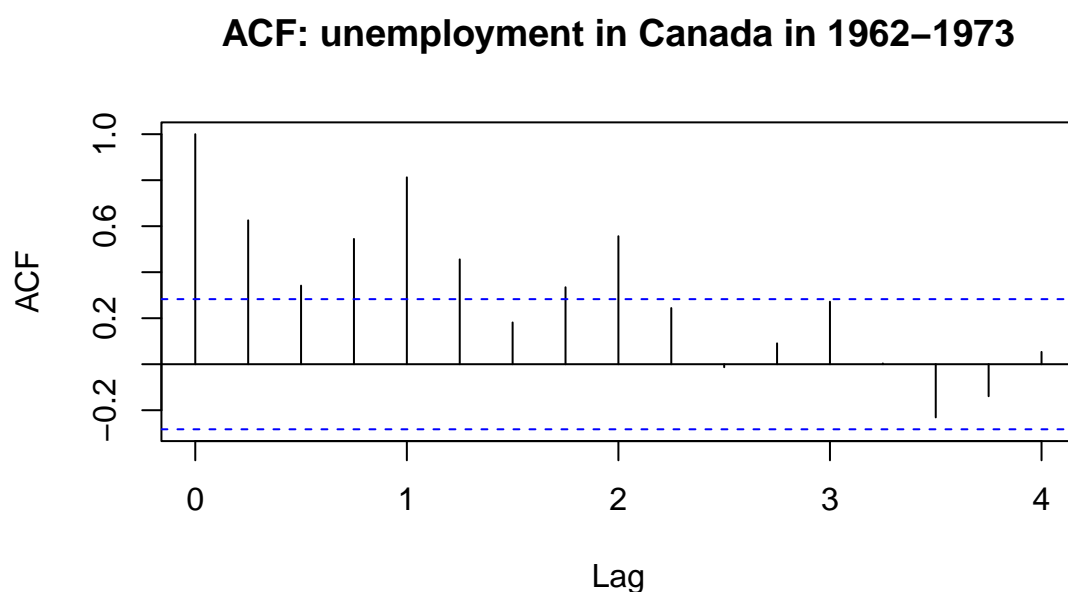


Figure 16: Autocorrelation Function (ACF) plot of the quarterly unemployment in Canada in 1962-1973

To address non-stationarity, differencing can stabilise the time series' mean and eliminate trends and seasonality. Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are conducted to determine the necessity of differencing objectively (R code 8.23).

Table 10: Augmented Dickey-Fuller (ADF) test of the training data

Augmented Dickey-Fuller Test

```
data: training_data
Dickey-Fuller = -1.9397, Lag order = 3, p-value = 0.5982
alternative hypothesis: stationary
```

The ADF test yields a high p-value (0.5982), failing to reject the null hypothesis of non-stationarity, while the KPSS test, with a p-value of 0.01, rejects the null hypothesis of stationarity around a level:

Table 11: Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test of the training data

#### KPSS Test for Level Stationarity

```
data: training_data
KPSS Level = 0.80281, Truncation lag parameter = 3, p-value = 0.01
```

As the next step, we can use `ndiffs()` and `nsdiffs()` functions to determine the appropriate number of first and seasonal differencing for the training data (R code 8.24):

```
Number of first differencings: 1
```

```
Number of seasonal differencings: 1
```

A Box-Cox transformation will not be performed due to the absence of evidence indicating variance changes.

Subsequently, the first and seasonal differencings are applied to the historical data, followed by an examination of the ACF/PACF plots in Figure 17 (R code 8.25).

The absence of significant spikes in the ACF plot beyond lag 0 suggests no need for autoregressive (AR) terms, while the significant spike at lag 1 in the PACF plot suggests a potential need for a Moving Average (MA) component.

## Differenced unemployment

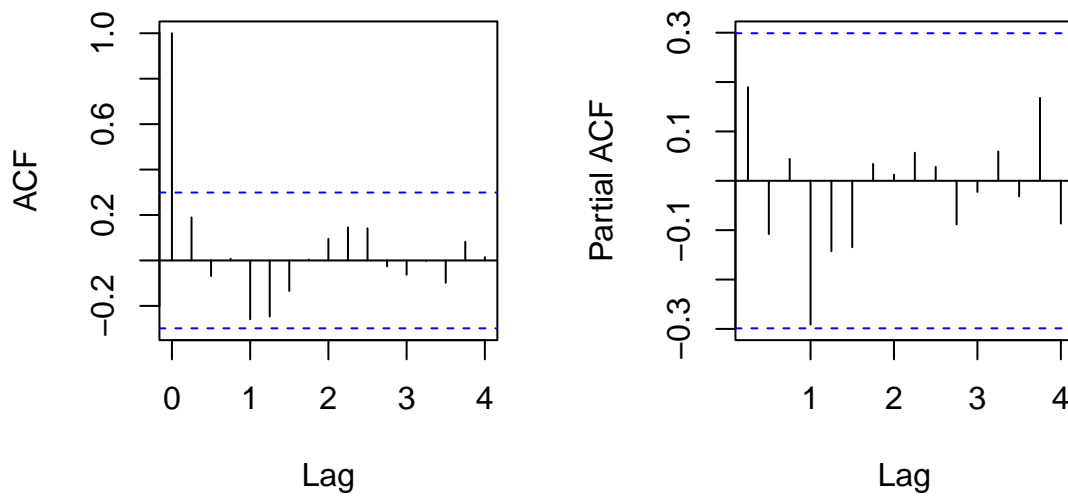


Figure 17: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the quarterly unemployment in Canada in 1962-1973

The efficacy of differencing is further confirmed by plotting the differenced historical data in Figure 18 together with performing the ADF test in Table 12, indicating stationarity of the differenced series, while the KPSS test in Table 13 fails to reject the null hypothesis of stationarity (R codes 8.26).

Table 12: Augmented Dickey-Fuller (ADF) test of the differenced data

### Augmented Dickey-Fuller Test

```
data: training_diff
Dickey-Fuller = -4.2479, Lag order = 3, p-value = 0.01
alternative hypothesis: stationary
```

Table 13: Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test of the differenced data

## KPSS Test for Level Stationarity

data: training\_diff

KPSS Level = 0.11986, Truncation lag parameter = 3, p-value = 0.1



Figure 18: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots of the differenced training data

With stationarity achieved, modeling using ARIMA (AutoRegressive Integrated Moving Average) methods becomes feasible. Based on observations, an initial ARIMA model of  $\text{ARIMA}(0,1,0)(1,1,0)[4]$  is proposed, accounting for differencing and seasonality (R code 8.27).

Table 14:  $\text{ARIMA}(0,1,0)(1,1,0)[4]$  model summary

Series: training\_data

$\text{ARIMA}(0,1,0)(1,1,0)[4]$

Coefficients:

```

      sar1
      -0.2806
s.e.    0.1504

```

```

sigma^2 = 97474:  log likelihood = -307.65
AIC=619.3   AICc=619.6   BIC=622.82

```

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-5.924679	292.0447	219.2004	0.2442629	5.699038	0.4779394	0.1445496

These statistical measures provide a way to compare the goodness of fit among different models. In this case, the log-likelihood is -307.65, and the AIC, AICc, and BIC are 619.3, 619.6, and 622.82, respectively. Lower values of AIC, AICc, and BIC indicate a better fit, suggesting that the model is relatively good compared to alternative models.

The seasonal autoregressive term (sar1) coefficient is -0.2806, indicating a negative relationship between the observations and their seasonal lagged values. This coefficient's standard error (s.e.) is 0.1504, suggesting a relatively precise estimate.

The MPE (Mean Percentage Error) is 0.2442629%, which measures the average relative error. It's close to 0, indicating that, on average, the model's forecasts are accurate.

Residual analysis in Figure 20 (R code 8.28) reveals normally distributed residuals with no significant autocorrelation, further affirming the adequacy of the ARIMA model.

Ljung-Box test

```

data:  Residuals from ARIMA(0,1,0)(1,1,0)[4]
Q* = 5.5894, df = 7, p-value = 0.5884

```

Model df: 1. Total lags used: 8

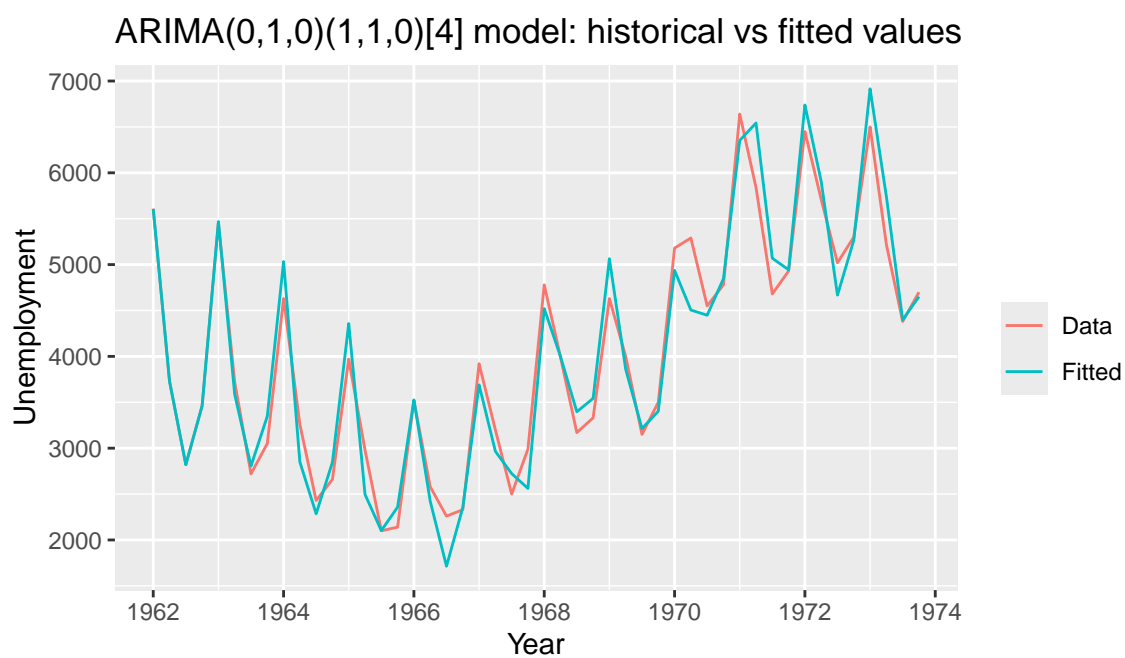


Figure 19: ARIMA(0,1,0)(1,1,0)[4] model: quarterly unemployment in Canada in 1962-1973 vs fitted values

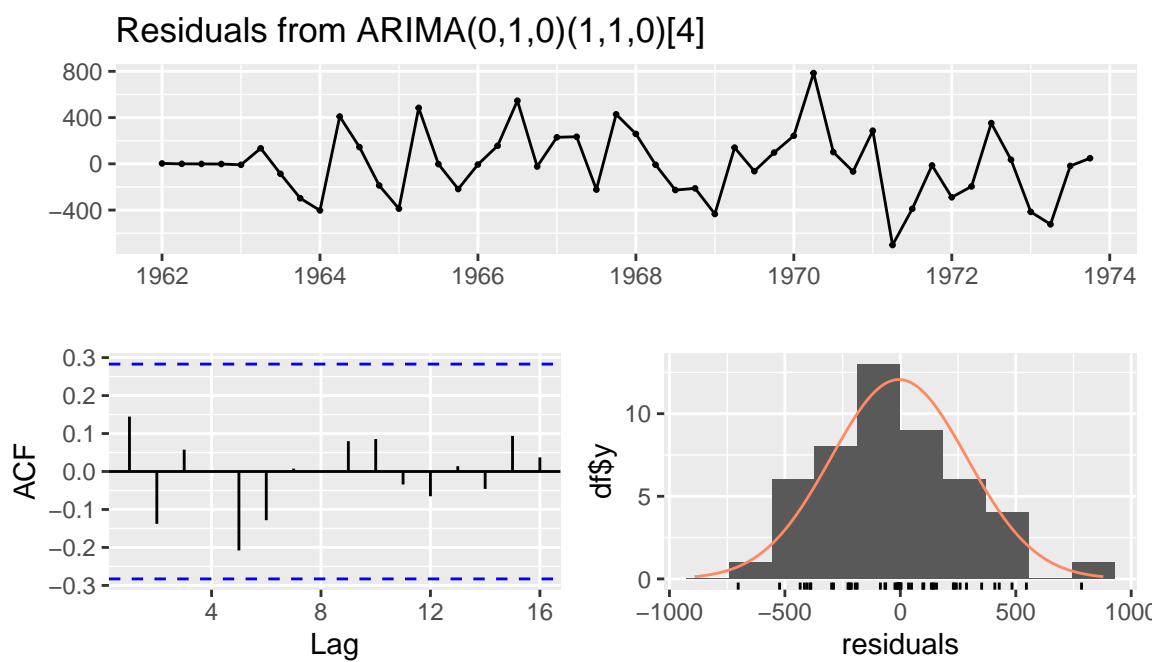


Figure 20: ARIMA(0,1,0)(1,1,0)[4] model: training residuals



The Ljung-Box test result, with a p-value of 0.5884, indicates that the model adequately captures the temporal dependence structure present in the historical data.

The Shapiro-Wilk test (R code 8.29), which assesses the normality of the residuals from the ARIMA model, does not provide sufficient evidence to reject the null hypothesis of normality. This suggests that the residuals from the ARIMA model are approximately normally distributed.

Table 15: Shapiro-Wilk test of the ARIMA model's training residuals

#### Shapiro-Wilk normality test

```
data:  arima_model$residuals
W = 0.98638, p-value = 0.8451
```

Upon forecasting performance evaluation against future data, the ARIMA model exhibits reasonably low errors and bias, indicating satisfactory performance, albeit challenges in predicting extraordinary spikes in future data in Figure 21 (R code 8.30).

The Ljung-Box Test Statistic's p-value (0.09731) rejects the null hypothesis of no autocorrelation in the residuals, suggesting no significant autocorrelation present in the residuals at the specified lags (R code 8.31).

#### Ljung-Box test

```
data:  Residuals
Q* = 6.3136, df = 3, p-value = 0.09731

Model df: 0.    Total lags used: 3
```

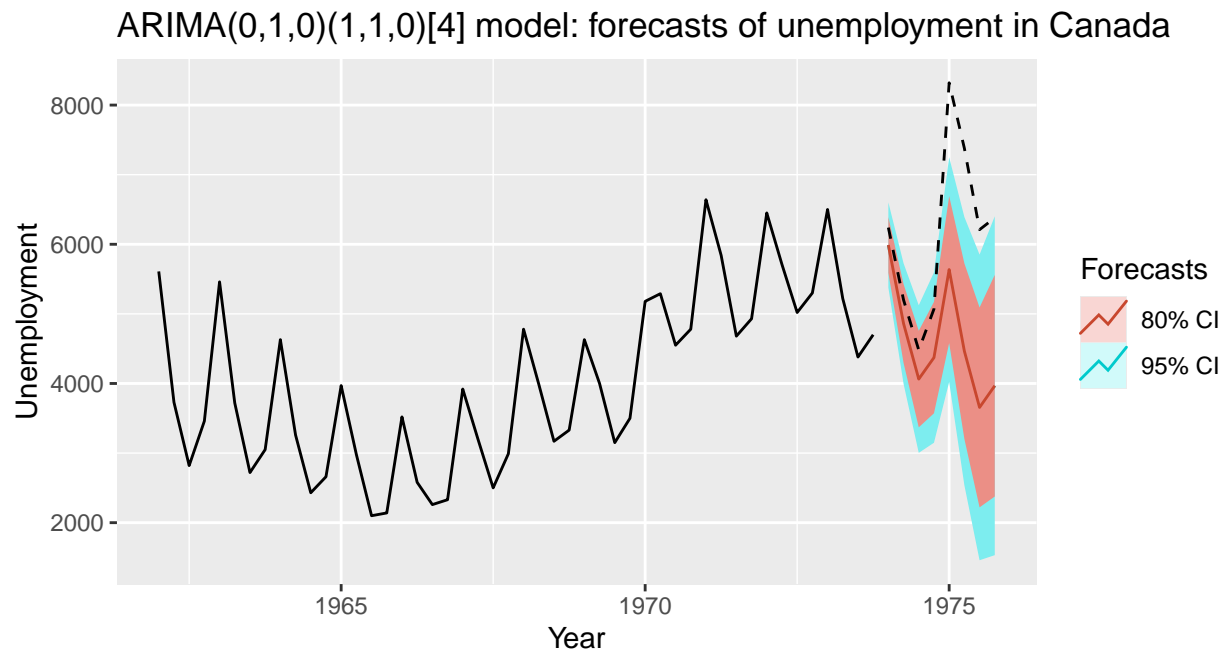


Figure 21: ARIMA(0,1,0)(1,1,0)[4] model's eight-quarter forecast of unemployment in Canada

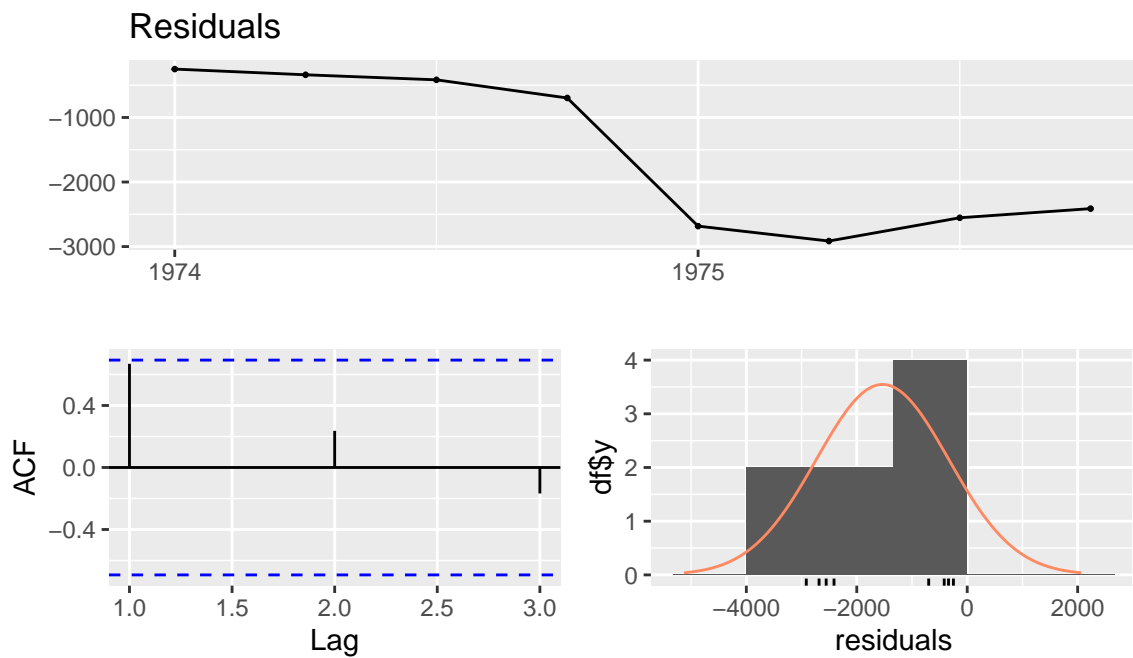


Figure 22: ARIMA(0,1,0)(1,1,0)[4] model: out-of-sample residuals

The metrics from Table 16 suggest that the model’s forecasts have relatively low errors and bias, indicating reasonably good performance, considering the future data had extraordinary spikes (R code 8.32).

Table 16: Error measures evaluating the ARIMA model’s out-of-sample accuracy

Mean Absolute Error (MAE)	1533.36923
Root Mean Squared Error (RMSE)	1899.72019
Mean Absolute Percentage Error (MAPE)	23.03253
Forecast Bias	-1533.36923

Comparative analysis of Mean Absolute Percentage Errors (MAPEs) among the three forecasting models helps identify the most suitable model (R code 8.33). It is a reasonable approach, especially if the models have different structures or complexities, such as the regression model, which includes polynomial terms. MAPE is a relative error metric that accounts for the magnitude of the forecasted values, which can be helpful when comparing models with different scales:

Table 17: Error measures evaluating out-of-sample accuracy of the three models

Model	MAE	RMSE	MAPE	Bias
ARIMA	1533.369	1899.720	23.03253	-1533.369
Exponential Smoothing	1975.517	2292.636	30.03790	-1975.517
Regression	1388.749	1812.552	20.50523	-1304.327

Best Model based on MAPE: Regression

However, it’s crucial to acknowledge that the three forecasting models struggled to forecast unemployment in Canada after 1975 due to the complex and multifaceted nature of the economic conditions during that period. The global economic recession, triggered by the oil

crisis of 1973-1974, resulted in stagnant growth and rising unemployment rates worldwide (Bank of Canada, 1999). Industrial restructuring, trade disruptions, and technological advancements further exacerbated job losses across various sectors. Government policies aimed at curbing inflation may have inadvertently worsened unemployment levels. The interplay of these factors created a highly volatile and uncertain economic environment, making it challenging for forecasting models to capture and predict unemployment dynamics during that time accurately.

## 5 Batch Forecasting

### 5.1 Exploratory analysis

In this section of the report, we undertake batch forecasting on a subset of quarterly time series data from the M3 competition, specifically focusing on IDs 1001 to 1100. It comprises historical data utilised for fitting automatic forecasting models and future data used to evaluate the forecasting performance of the fitted models. Each time series represents a historical record of a specific variable, such as sales numbers, stock prices, or production levels. For instance, the time series with ID 1001 tracks the volume indices of exports (both goods and services) from Japan (R code 8.34).

Table 18: M3 competition series ID 1001

Series: Q356

Type of series: MACRO

Period of series: QUARTERLY

Series description: OECD ECONOMIC OUTLOOK - JAPAN Export(Goods-Services)- Volume Indices

HISTORICAL data

	Qtr1	Qtr2	Qtr3	Qtr4
1980	3311.5	3368.0	3363.0	3504.0

1981	3609.5	3848.0	4018.5	3980.5
1982	4016.0	4009.0	4053.0	4002.5
1983	3928.0	3983.0	4140.5	4305.0
1984	4481.5	4630.5	4739.0	4934.0
1985	4923.5	5135.5	4987.0	4951.5
1986	4692.0	4793.5	4681.0	4774.5
1987	4791.5	4839.0	5047.5	5140.0
1988	5198.0	5257.0	5713.0	5772.5
1989	5965.0	6168.0	6473.0	6638.0
1990	6928.5	7034.0	6874.5	7055.0

FUTURE data

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7246.5	7146.0	7357.0	7469.0
1992	7507.5	7380.0	7449.5	7587.5

The primary objective of this section of the report is to select, automatically fit, and evaluate three distinct statistical models (ARIMA, ETS, and TBATS) for forecasting quarterly time series of IDs from 1001 to 1100 from the M3 competition data set.

## 5.2 Error measures selection

Following the generation of forecasts for the next eight quarters, we will assess their accuracy using two appropriate error measures:

**Mean Absolute Percentage Error (MAPE)** measures the percentage difference between the actual future and forecasted values, offering a relative measure of forecast accuracy. MAPE represents the average percentage error of the forecast relative to the future data. Its simplicity makes it easy to understand and communicate to stakeholders.

**Symmetric Mean Absolute Percentage Error (sMAPE)** measures the percentage difference between future and forecasted values in a symmetric manner, meaning it does not

favour overestimation or underestimation. It calculates the absolute percentage error for each observation and then averages these errors across all observations. sMAPE is scale-independent, allowing for comparison of forecast accuracy across different data sets and variables. Its symmetry treats positive and negative errors equally, which can be advantageous in various forecasting scenarios.

While MAPE offers simplicity and straightforwardness, sMAPE provides additional robustness and symmetry, rendering it suitable for a broader range of forecasting scenarios. Both measures are valuable for comparing forecast accuracy across different time series with varying scales, aiding in comprehensive evaluation and decision-making processes.

### 5.3 Benchmarking

In addition to evaluating each model's accuracy using MAPE and sMAPE, we will compare their performance against two benchmark methods:

**Theta model** considers both the level and trend of the time series data. Theta forecasting provides a straightforward baseline for comparison, capturing basic trends in the data without incorporating more complex patterns. One advantage of Theta forecasting is its simplicity and ease of implementation, making it suitable for quick assessments of forecasting performance. According to Makridakis and Hibon (2000), despite its apparent simplicity and lack of reliance on robust statistical foundations, the Theta method exhibits remarkable accuracy across various series types, forecasting timeframes, and evaluation metrics. However, it may overlook more subtle patterns or seasonality in the data, limiting its accuracy compared to more sophisticated models.

**Damped Exponential Smoothing** is a variation of exponential smoothing that diminishes the influence of past observations as the forecast horizon extends. This method accounts for the decreasing relevance of historical data as time progresses, offering a more nuanced approach than the theta model's simplicity. Damped exponential smoothing is advantageous as it adapts to changing data patterns over time, providing smoother and often more accurate forecasts. However, it may struggle with abrupt changes or outliers in the data, potentially

leading to inaccuracies in forecasting during periods of volatility.

By comparing the performance of the models against these benchmark methods, we can gain insights into their relative effectiveness and assess their ability to outperform basic forecasting approaches. This comparative analysis will aid in identifying the strengths and weaknesses of each model, guiding decision-making processes and informing future forecasting strategies.

## 5.4 Automatic ARIMA model

The `auto.arima()` function in R automatically selects the optimal ARIMA parameters for each time series data (IDs 1001 to 1100) from the M3 competition data set based on the corrected Akaike Information Criterion (AICc) (R code 8.35)<sup>1</sup>. However, it may not effectively capture complex seasonal patterns or structural changes in the data, leading to suboptimal forecasts in certain cases. The automatic ARIMA model may also struggle with noisy or irregular data, requiring additional preprocessing or model refinement to improve forecasting accuracy.

After computing the average Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (sMAPE) for the ARIMA models, we compare its performance with the Theta and Damped Exponential Smoothing models, which serve as benchmarks (R code 8.36). Individual error values are calculated for each method across multiple time series.

Table 19: Error measures evaluating automatic ARIMA model's out-of-sample accuracy

Model	MAPE	sMAPE
ARIMA	5.683726	5.370717
Theta	5.541910	5.291370
Damped Exponential Smoothing	4.672529	4.539832

Best model based on MAPE: Damped Exponential Smoothing

---

<sup>1</sup>Appendix 8.35 contains a comprehensive list of automatically fitted ARIMA models for each series and their respective forecasted values.

### Best model based on sMAPE: Damped Exponential Smoothing

The ARIMA model's forecasts have an absolute percentage error of approximately 5.68%, with a symmetric perspective suggesting a slightly lower error of around 5.37%.

The Theta forecast model's predictions demonstrate a lower absolute percentage error than the ARIMA model while showing a slightly lower error from a symmetric perspective.

Conversely, the Damped Exponential Smoothing model displays the lowest average MAPE of around 4.67% and the lowest average sMAPE of about 4.54%. These results indicate that the Damped Exponential Smoothing model offers the most accurate forecasts among the three methods, with both MAPE and sMAPE indicating lower error rates than the ARIMA and Theta forecast models.

## 5.5 Automatic Error-Trend-Seasonality (ETS) model

The `ets()` function in R automatically selects the optimal ETS (Error, Trend, Seasonality) model based on each series' data characteristics, such as the presence of trend and seasonality. The fitted ETS model contains information about the estimated parameters, including the level, trend, and seasonal components for each series and any additional settings or options specified during the fitting process (R code 8.37)<sup>2</sup>. However, it may be computationally intensive for large-scale forecasting tasks and could produce suboptimal results if the underlying data contains irregular patterns or outliers.

Similarly to the auto ARIMA model, we calculate the average Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (sMAPE) for the ETS forecasting models and compare them with the metrics for Theta and Damped Exponential Smoothing models as benchmarks (R code 8.38).

Table 20: Error measures evaluating automatic ETS model's out-of-sample accuracy

---

<sup>2</sup>Appendix 8.37 contains a comprehensive list of automatically fitted ETS models for each series and their respective forecasted values.



Model	MAPE	sMAPE
ETS	5.140505	4.936170
Theta	5.541910	5.291370
Damped Exponential Smoothing	4.672529	4.539832

Best model based on MAPE: Damped Exponential Smoothing

Best model based on sMAPE: Damped Exponential Smoothing

The ETS model exhibits a MAPE of 5.14%, indicating that, on average, its forecasts have a percentage error of approximately 5.14% compared to the future values. Additionally, it has an sMAPE of 4.94%, suggesting that, on average, its forecasts have a symmetric percentage error of approximately 4.94% compared to the future data.

Although the Damped Exponential Smoothing model slightly outperforms the ETS model, the latter still exhibits superior accuracy compared to the Theta model. Therefore, the ETS model remains a reliable choice for forecasting, especially considering its competitive performance. Factors such as computational simplicity or model interpretability may further support selecting the ETS model for forecasting tasks.

## **5.6 Automatic Trigonometric Seasonal Box-Cox Transformation, ARMA errors, Trend, and Seasonal components (TBATS) model**

The TBATS model is renowned for its capability to handle multiple seasonalities, trends, and complex patterns in time series data (Brozyna, Mentel and Szetela, 2016). It is particularly useful for data sets with intricate seasonal patterns and irregular trends. It is preferred for automatic forecasting tasks where data may exhibit multiple seasonalities and nonlinear patterns. However, it may suffer from computational intensity, especially with large data sets, and might require tuning parameters for optimal performance in certain cases.

TBATS decomposes the time series into components, including multiple seasonalities and trends, utilising trigonometric functions and Box-Cox transformations. Subsequently, it fits an ARMA model to the residuals to capture any remaining temporal dependencies, providing forecasts based on the estimated components and model parameters (R code 8.39)<sup>3</sup>.

Similar to the auto ARIMA and ETS models, we compute the average Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (sMAPE) for the TBATS forecasting models and compare them with the metrics for Theta and Damped Exponential Smoothing models as benchmarks (R code 8.40).

Table 21: Error measures evaluating automatic TBATS model's out-of-sample accuracy

Model	MAPE	sMAPE
TBATS	6.156728	5.829611
Theta	5.541910	5.291370
Damped Exponential Smoothing	4.672529	4.539832

Best model based on MAPE: Damped Exponential Smoothing

Best model based on sMAPE: Damped Exponential Smoothing

The TBATS model shows an average MAPE of about 6.16% and an sMAPE of around 5.83%. However, the Damped Exponential Smoothing and Theta models outperform it, with average MAPEs of 4.67% and 5.54% and sMAPEs of 4.54% and 5.29%, respectively.

To summarise the above, we output the average MAPE and sMAPE values for the automatic ARIMA, ETS, and TBATS models alongside their benchmark models (Theta and Damped Exponential Smoothing) to determine the best-performing model. The results are sorted in ascending order based on their combined performance in both MAPE and sMAPE (R code 8.41).

---

<sup>3</sup>Appendix 8.39 contains a comprehensive list of automatically fitted TBATS models for each series and their respective forecasted values.

Table 22: Error measures evaluating out-of-sample accuracy of the automatic models

Method	MAPE	sMAPE
Damped Exponential Smoothing	4.672529	4.539832
ETS	5.140505	4.936170
Theta	5.541910	5.291370
ARIMA	5.683726	5.370717
TBATS	6.156728	5.829611

Best model based on MAPE and sMAPE:

Method	MAPE	sMAPE
Damped Exponential Smoothing	4.672529	4.539832

The analysis reveals that the Damped Exponential Smoothing method emerges as the best model, boasting the lowest MAPE and sMAPE values of 4.67% and 4.54%, respectively. This indicates that, on average, this method provides the most accurate forecasts compared to the others evaluated.

Conversely, the TBATS method exhibits the highest MAPE (6.16%) and sMAPE (5.83%) values, indicating the least accurate forecasting performance among all the evaluated methods. The TBATS model might perform worse due to factors such as potential overfitting, violation of model assumptions, and limitations in historical data. These issues can collectively hinder the model's accuracy and effectiveness in forecasting.

## 6 Conclusions

This report has provided valuable insights into the performance and effectiveness of various forecasting methods for quarterly time series data.

Although the 1975 recession significantly impacted forecast accuracy, and the manual models struggled to anticipate the abrupt shifts in unemployment rates during this economic turmoil, the forecasts before the recession yielded promising results, with the regression model exhibiting superior accuracy.

The competitive edge of the Damped Exponential Smoothing model over automatic ARIMA, ETS, and TBATS models for batch forecasting can be attributed to the factor highlighted by Koning, Franses, Hibon and Stekler (2005) that the complexity of forecasting methods does not always correlate with forecast accuracy.

It is crucial to acknowledge the inherent limitations in forecasting, including the reliance on historical data and assumptions regarding stationarity and underlying patterns. Moving forward, continued research and experimentation are essential to refining forecasting methodologies and addressing the evolving challenges posed by dynamic and uncertain environments.

By leveraging the insights from this study, organisations can enhance their forecasting capabilities and make informed decisions to navigate the complexities of today’s business landscape effectively. By strategically utilising forecasting techniques, businesses can optimise resource allocation, minimise risks, and seize opportunities for growth and innovation.

---

## 7 References

Bank of Canada (1999) *Canadian economic performance at the end of the twentieth century*. Available at: <https://www.bankofcanada.ca/1999/06/canadian-economic-performance-end-twentieth-century/> (Accessed: 29 March 2024).

Brozyna J., Mentel G., Szetela B. (2016), ‘Influence of double seasonality on economic forecasts on the example of energy demand’, *Journal of International Studies*, Vol. 9, No 3, pp. 9-20. Available at: <https://doi.org/10.14254/2071-8330.2016/9-3/1>.

Koning, A.J., Franses, P.H., Hibon, M. and Stekler, H.O. (2005) ‘The M3 competition: Statistical tests of the results’, *International Journal of Forecasting*, 21(3), pp.397–409. Available at: <https://doi.org/10.1016/j.ijforecast.2004.10.003>.

Makridakis, S. and Hibon, M. (2000) ‘The M3-Competition: results, conclusions and implications’, *International Journal of Forecasting*, 16(4), pp.451–476. Available at: [https://doi.org/10.1016/s0169-2070\(00\)00057-1](https://doi.org/10.1016/s0169-2070(00)00057-1).

## 8 Appendices

### 8.1 Code displaying series ID 1394 of the M3 competition data set

```
frequency <- 4 ## for quarterly time series
data <- M3[[1394]]
data <- subset(data, frequency == frequency)
cat("Table 1: M3 competition series ID 1394")
data
```

### 8.2 Codes producing a time series plot of the historical data (Figure 1) and its summary

```
# Assign the historical data to a variable for training the model
training_data <- data$x
# Assign the future data points for testing the model's predictions
test_data <- data$xx
```

```
# Generate a time series plot of the training data
```

```
autoplot(training_data,  
  type = "l",  
  xlab = "Year",  
  ylab = "Unemployment",  
  main = "Quarterly unemployment in Canada in 1962-1973  
(Series ID 1394)")
```

```
cat("Table 2: Summary of the quarterly unemployment in Canada in 1962-1973")  
summary(training_data)
```

### 8.3 Codes producing the seasonality plot (Figure 2) and the seasonal subseries plot of the training data (Figure 3)

```
ggseasonplot(training_data, year.labels=TRUE, year.labels.left=TRUE) +  
  ylab("Unemployment") +  
  ggtitle("Seasonality: quarterly unemployment in Canada")
```

```
ggsubseriesplot(training_data) +  
  ylab("Unemployment") +  
  ggtitle("Seasonal subseries: quarterly unemployment in Canada")
```

### 8.4 Code producing the lagged scatter plots of the quarterly Canadian unemployment in 1962-1973 (Figure 4)

```
gglagplot(training_data) +  
  #ggtitle("Lagged scatter plot: quarterly unemployment") +
```

```
theme(legend.position = "bottom",
      axis.text.x = element_text(angle = 45, hjust = 1))
```

## 8.5 Code plotting the Autocorrelation Function (ACF) of the quarterly unemployment in Canada in 1962-1973 in Figure 5

```
ggAcf(training_data, main = "ACF: unemployment in Canada in 1962-1973")
```

## 8.6 Code plotting multiplicative decomposition of the quarterly unemployment in Canada in 1962-1973 in Figure 6

```
training_decomposed <- decompose(training_data, type = "multiplicative")
autoplot(training_decomposed) + xlab("Year")
```

## 8.7 Code producing box plots of unemployment in Canada in 1962-1973 per quarter in Figure 7 to detect outliers

```
# Ensure the time series has the correct frequency set
training_ts <- ts(training_data, frequency = 4)

# Convert the time series to a data frame for plotting
# Create a factor indicating the quarter
df <- data.frame(
  Value = as.numeric(training_ts),
  Quarter = factor(rep(1:4, length.out = length(training_ts)))
)
```

```
ggplot(df, aes(x = Quarter, y = Value)) +
  geom_boxplot() +
  labs(title = "Distribution of unemployment in Canada in 1962-1973",
       x = "Quarter", y = "Unemployment")
```

## 8.8 Code fitting a polynomial regression model using the `tslm()` function

```
# Regression Model
regression_model <- tslm(training_data ~ trend +
                        I(trend^2) + I(trend^3) + season)
cat("Table 3: Regression model summary")
summary(regression_model)
```

## 8.9 Code plotting the training data and values fitted by the regression model in Figure 8

```
autoplot(training_data, series="Data") +
  autolayer(fitted(regression_model), series="Fitted") +
  xlab("Year") + ylab("Unemployment") +
  ggtitle("Regression model: historical vs fitted values") +
  guides(color = guide_legend(title = ""))
```

## 8.10 Code running the Shapiro-Wilk test checking the assumption of normality of the regression model's training residuals



```
cat("Table 4: Shapiro-Wilk test of the regression model's training residuals")
shapiro.test(regression_model$residuals)
```

### 8.11 Code plotting training residuals from the regression model in Figure 9

```
checkresiduals(regression_model)
```

### 8.12 Code running the Ljung-Box test detecting autocorrelation in the training residuals at lag 1

```
# Perform Ljung-Box test on the residuals
ljung_box_test <- Box.test(regression_model$residuals, lag = 1,
                           type = "Ljung-Box")

# Print the results
cat("Table 5: Box-Ljung test of the regression model's training residuals")
ljung_box_test
```

### 8.13 Code plotting future (out-of-sample) data and values forecasted by the regression model in Figure 10

```
# Forecast
forecast_regression <- forecast(regression_model, h = 8,
                                PI = TRUE, level = c(0.8, 0.95))
```

```
# Plot the forecast and test data together
autoplot(training_data) +
  autolayer(forecast(regression_model, level = c(0.95)),
    series = "95% CI") +
  autolayer(forecast(regression_model, level = c(0.8)),
    series = "80% CI") +
  autolayer(test_data, color = "black", linetype = "dashed",
    series = "Future Data") +
  xlab("Year") +
  ylab("Unemployment") +
  ggtitle("Regression model: forecasts of unemployment in Canada") +
  guides(color = guide_legend(title = "Forecasts"),
    linetype = guide_legend(title = "Future Data"))
```

#### 8.14 Code plotting out-of-sample residuals from the regression model in Figure 11

```
residuals_regression <- forecast_regression$mean - test_data
checkresiduals(residuals_regression)
```

#### 8.15 Code calculating measures, such as MAE, RMSE, and MAPE, to evaluate the accuracy of the regression model to forecast future data

```
# Calculate evaluation metrics
mae_regression <- mean(abs(residuals_regression))
rmse_regression <- sqrt(mean(residuals_regression^2))
```

```

mape_regression <- mean(abs(residuals_regression / test_data)) * 100
bias_regression <- mean(residuals_regression)

# Create a data frame for the metrics
evaluation_regression <- data.frame(
  Metric = c("Mean Absolute Error (MAE)",
             "Root Mean Squared Error (RMSE)",
             "Mean Absolute Percentage Error (MAPE)",
             "Forecast Bias"),
  Value = c(mae_regression,
            rmse_regression,
            mape_regression,
            bias_regression)
)

# Remove column names
colnames(evaluation_regression) <- NULL

# Print the data frame
cat("Table 6: Error measures evaluating the regression model's
    out-of-sample accuracy")
print(evaluation_regression, row.names = FALSE, col.names = FALSE)

```

8.16 Code fitting and plotting in Figure 12 the exponential smoothing model with the Holt-Winters method, incorporating multiplicative error, additive trend with damping, and multiplicative seasonality components (ETS(M,Ad,M))

```
# Fit the Holt-Winters model with multiplicative trend and seasonality
hw_model <- ets(training_data, model="MAM", damped=TRUE)
cat("Table 7: Exponential Smoothing model with
    the Holt-Winters method summary")
summary(hw_model)
```

```
autoplot(training_data, series="Data") +
  autolayer(fitted(hw_model), series="Fitted") +
  xlab("Year") + ylab("Unemployment") +
  ggtitle("ETS (M, Ad, M) model: historical vs fitted values") +
  guides(color = guide_legend(title = ""))
```

8.17 Code plotting training residuals of the exponential smoothing (ETS (M, Ad, M)) model in Figure 13

```
checkresiduals(hw_model)
```

8.18 Code running the Shapiro-Wilk test of the exponential smoothing model's training residuals

```
# Test for normality
cat("Table 8: Shapiro-Wilk test of the exponential
    smoothing model's training residuals")
shapiro.test(hw_model$residuals)
```

## 8.19 Code plotting the forecast of the exponential smoothing model with the Holt-Winters method against future data in Figure 14

```
# Forecast
forecast_hw <- forecast(hw_model, h = 8,
                        PI = TRUE, level = c(0.8, 0.95))

# Plot the forecast and test data together
autoplot(training_data) +
  autolayer(forecast(hw_model, level = c(0.95)),
            series = "95% CI") +
  autolayer(forecast(hw_model, level = c(0.8)),
            series = "80% CI") +
  autolayer(test_data, color = "black", linetype = "dashed",
            series = "Future Data") +
  xlab("Year") +
  ylab("Unemployment") +
  ggtitle("ETS(M,Ad,M) model: forecasts of unemployment in Canada") +
  guides(color = guide_legend(title = "Forecasts"),
         linetype = guide_legend(title = "Future Data"))
```

## 8.20 Code plotting out-of-sample residuals of the exponential smoothing (ETS (M, Ad, M)) model in Figure 15

```
# Calculate residuals
residuals_hw <- forecast_hw$mean - test_data
checkresiduals(residuals_hw)
```

## 8.21 Code calculating measures, such as MAE, RMSE, and MAPE, to evaluate the accuracy of the exponential smoothing (ETS (M, Ad, M)) model to forecast future data

```
# Calculate evaluation metrics
mae_hw <- mean(abs(residuals_hw))
rmse_hw <- sqrt(mean(residuals_hw^2))
mape_hw <- mean(abs(residuals_hw / test_data)) * 100
bias_hw <- mean(residuals_hw)

# Create a data frame for the metrics
evaluation_hw <- data.frame(
  Metric = c("Mean Absolute Error (MAE)",
             "Root Mean Squared Error (RMSE)",
             "Mean Absolute Percentage Error (MAPE)",
             "Forecast Bias"),
  Value = c(mae_hw, rmse_hw, mape_hw, bias_hw)
)

# Remove column names
colnames(evaluation_hw) <- NULL
```

```
# Print the data frame
cat("Table 9: Error measures evaluating ETS(M,Ad,M) model's
    out-of-sample accuracy")
print(evaluation_hw, row.names = FALSE, col.names = FALSE)
```

## 8.22 Code plotting the Autocorrelation Function (ACF) in Figure 16

```
acf(training_data, main = "ACF: unemployment in Canada in 1962-1973")
```

## 8.23 Code conducting the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests to determine the necessity of differencing

```
library(tseries)
cat("Table 10: Augmented Dickey-Fuller (ADF) test of the training data")
adf.test(training_data, alternative = "stationary")
```

```
library(urca)
cat("Table 11: Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test
    of the training data")
kpss.test(training_data)
```

## 8.24 Code determining the appropriate number of first and seasonal differencing for the training data

```
cat("Number of first differencings: ", ndiffs(training_data))  
  
cat("Number of seasonal differencings: ", nsdiffs(training_data))
```

## 8.25 Code plotting the ACF/PACF functions for the differenced training data in Figure 17

```
training_diff <- diff(diff(training_data, differences = 1), lag = 4)  
  
# Set up a multi-panel plot with 1 row and 2 columns  
par(mfrow = c(1, 2))  
  
# Plot ACF for differenced data  
acf(training_diff, main = "Differenced unemployment")  
  
# Plot PACF for differenced data  
pacf(training_diff, main = "")
```

## 8.26 Codes plotting the differenced historical data in Figure 18 together with performing the ADF and the KPSS tests

```
cat("Table 12: Augmented Dickey-Fuller (ADF) test of the differenced data")  
adf.test(training_diff, alternative = "stationary")
```



```
cat("Table 13: Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test
    of the differenced data")
kpss.test(training_diff)
```

```
# Plot Differenced Data
autoplot(training_diff)+
  ggtitle("Differenced unemployment in Canada in 1962-1973") +
  xlab("Year")+
  ylab("Differenced unemployment")+
  guides(color = guide_legend(title = ""))
```

## 8.27 Code fitting and plotting ARIMA(0,1,0)(1,1,0)[4] model in Figure 19

```
cat("Table 14: ARIMA(0,1,0)(1,1,0)[4] model summary")
arima_model <- Arima(training_data, order = c(0,1,0), seasonal = c(1,1,0))
summary(arima_model)
```

```
autoplot(training_data, series="Data") +
  autolayer(fitted(arima_model), series="Fitted") +
  xlab("Year") + ylab("Unemployment") +
  ggtitle("ARIMA(0,1,0)(1,1,0)[4] model: historical vs fitted values") +
  guides(color = guide_legend(title = ""))
```

## 8.28 Code plotting residual analysis in Figure 20

```
# Plot histogram of residuals
checkresiduals(arima_model)
```

## 8.29 Code conducting the Shapiro-Wilk test assessing the normality of the residuals from the ARIMA model

```
# Test for normality
cat("Table 15: Shapiro-Wilk test of the ARIMA model's training residuals")
shapiro.test(arima_model$residuals)
```

## 8.30 Code plotting ARIMA(0,1,0)(1,1,0)[4] model's eight-quarter forecast of unemployment in Canada in Figure 21

```
# Forecast
forecast_arima <- forecast(arima_model, h = 8,
                           PI = TRUE, level = c(0.8, 0.95))

# Plot the forecast and test data together
autoplot(training_data) +
  autolayer(forecast(arima_model, level = c(0.95)),
            series = "95% CI") +
  autolayer(forecast(arima_model, level = c(0.8)),
            series = "80% CI") +
  autolayer(test_data, color = "black", linetype = "dashed",
            series = "Future Data") +
  xlab("Year") +
  ylab("Unemployment") +
  ggtitle("ARIMA(0,1,0)(1,1,0)[4] model: forecasts of unemployment in
          Canada") +
  guides(color = guide_legend(title = "Forecasts"),
         linetype = guide_legend(title = "Future Data"))
```

### 8.31 Code conducting the Ljung-Box test and plotting the residual analysis in Figure 20

```
# Calculate residuals
residuals_arima <- forecast_arima$mean - test_data

checkresiduals(residuals_arima)
```

### 8.32 Code evaluating the ARIMA model's forecasting accuracy

```
# Calculate evaluation metrics
mae_arima <- mean(abs(residuals_arima))
rmse_arima <- sqrt(mean(residuals_arima^2))
mape_arima <- mean(abs(residuals_arima / test_data)) * 100
bias_arima <- mean(residuals_arima)

# Create a data frame for the metrics
evaluation_arima <- data.frame(
  Metric = c("Mean Absolute Error (MAE)", "Root Mean Squared Error (RMSE)",
             "Mean Absolute Percentage Error (MAPE)", "Forecast Bias"),
  Value = c(mae_arima, rmse_arima, mape_arima, bias_arima)
)

# Remove column names
colnames(evaluation_arima) <- NULL

# Print the data frame
cat("Table 16: Error measures evaluating the ARIMA model's")
```

```

    out-of-sample accuracy")
print(evaluation_arima, row.names = FALSE, col.names = FALSE)

```

### 8.33 Code comparing Mean Absolute Percentage Errors (MAPEs) among the three forecasting models

```

# Store evaluation metrics for each model in a data frame
evaluation_metrics <- data.frame(
  Model = c("ARIMA", "Exponential Smoothing", "Regression"),
  MAE = c(mae_arima, mae_hw, mae_regression),
  RMSE = c(rmse_arima, rmse_hw, rmse_regression),
  MAPE = c(mape_arima, mape_hw, mape_regression),
  Bias = c(bias_arima, bias_hw, bias_regression)
)

# Print the evaluation metrics for comparison
cat("Table 17: Error measures evaluating
    out-of-sample accuracy of the three models")
print(evaluation_metrics, row.names = FALSE)

# Select the model with the lowest values for the evaluation metrics
best_model <- evaluation_metrics[which.min(evaluation_metrics$MAPE), ]

# Print the best model
cat("Best Model based on MAPE:", best_model$Model, "\n")

```

### 8.34 Code printing M3 competition series ID 1001

```
cat("Table 18: M3 competition series ID 1001")  
M3[[1001]]
```

### 8.35 Code printing summaries of automatically fitted ARIMA models for each series (IDs 1001 to 1100) using `auto.arima()` function and printing respective forecasted values.

```
# Define the series IDs and criterion  
ts_start <- 1001  
ts_end <- 1100  
criterion <- "aicc"  
num_ts <- ts_end - ts_start + 1  
  
# Initialize arrays to store MAPE and sMAPE for ARIMA and benchmarks  
mape_arima <- numeric(num_ts)  
mape_theta <- numeric(num_ts)  
mape_damped <- numeric(num_ts)  
smape_arima <- numeric(num_ts)  
smape_theta <- numeric(num_ts)  
smape_damped <- numeric(num_ts)  
  
# Loop through each time series  
for (s in ts_start:ts_end) {  
  train_data <- M3[[s]]$x  
  test_data <- M3[[s]]$xx  
  h <- length(test_data)
```

```

# Fit ARIMA model
arima_fit <- auto.arima(train_data, ic = criterion)
# Print summary of the fitted ARIMA model
cat("Summary for ARIMA model of Time Series ID:", s, "\n")
print(summary(arima_fit))
cat("\n") # Add a newline after each summary

arima_fcst <- forecast(arima_fit, h = h)$mean
# Print forecasts
cat("Forecasts for Time Series ID:", s, "\n")
print(arima_fcst)
cat("\n") # Add a newline after printing forecasts

# Calculate MAPE for ARIMA
mape_arima[s - ts_start + 1] <- 100 * mean(abs(test_data - arima_fcst) /
                                           test_data, na.rm = TRUE)

# Calculate sMAPE for ARIMA
smape_arima[s - ts_start + 1] <- 200 * mean(abs(test_data - arima_fcst) /
                                           (abs(test_data) + abs(arima_fcst)),
                                           na.rm = TRUE)

# Fit Theta model
theta_fit <- thetaf(train_data, h = h)
theta_fcst <- forecast(theta_fit)$mean
# Calculate MAPE for Theta
mape_theta[s - ts_start + 1] <- 100 * mean(abs(test_data - theta_fcst) /
                                           test_data, na.rm = TRUE)

# Calculate sMAPE for Theta
smape_theta[s - ts_start + 1] <- 200 * mean(abs(test_data - theta_fcst) /
                                           (abs(test_data) + abs(theta_fcst)),
                                           na.rm = TRUE)

```

```

na.rm = TRUE)

# Fit Damped Exponential Smoothing model
tryCatch({
  damped_model <- ets(train_data, model = "ZZZ", damped = TRUE)
  damped_fcst <- forecast(damped_model, h = h)$mean
  # Calculate MAPE for Damped Exponential Smoothing
  mape_damped[s - ts_start + 1] <- 100 * mean(abs(test_data - damped_fcst) /
                                              test_data, na.rm = TRUE)

  # Calculate sMAPE for Damped Exponential Smoothing
  smape_damped[s - ts_start + 1] <- 200 * mean(abs(test_data - damped_fcst) /
                                              (abs(test_data) + abs(damped_fcst)),
                                              na.rm = TRUE)

}, error = function(e) {
  mape_damped[s - ts_start + 1] <- NA # Assign NA in case of error
  smape_damped[s - ts_start + 1] <- NA # Assign NA in case of error
})
}

```

Summary for ARIMA model of Time Series ID: 1001

Series: train\_data

ARIMA(0,1,0)(0,0,2)[4] with drift

Coefficients:

	sma1	sma2	drift
	0.2285	-0.4830	80.6054
s.e.	0.1756	0.1934	14.4313

sigma^2 = 13956: log likelihood = -266.13

AIC=540.26 AICc=541.31 BIC=547.31

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.4883693	112.6361	93.57038	-0.09058363	1.927003	0.224302

ACF1

Training set 0.1312772

Forecasts for Time Series ID: 1001

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7117.925	7120.625	7067.545	7143.754
1992	7162.699	7255.612	7410.836	7444.435

Summary for ARIMA model of Time Series ID: 1002

Series: train\_data

ARIMA(1,2,1)

Coefficients:

	ar1	ma1
	-0.5437	-0.8493
s.e.	0.1586	0.0899

$\sigma^2 = 13034$ : log likelihood = -258.74

AIC=523.49 AICc=524.12 BIC=528.7

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	34.36251	108.8543	84.01765	0.7305779	1.701211	0.3224008	0.08323809

Forecasts for Time Series ID: 1002

	Qtr1	Qtr2	Qtr3	Qtr4
--	------	------	------	------



1991 6768.023 6821.732 6923.182 6998.677  
1992 7088.283 7170.218 7256.323 7340.161

Summary for ARIMA model of Time Series ID: 1003

Series: train\_data

ARIMA(0,1,0)(0,0,1)[4] with drift

Coefficients:

	sma1	drift
	-0.2844	59.9585
s.e.	0.1900	19.2528

sigma^2 = 30222: log likelihood = -281.96

AIC=569.92 AICc=570.54 BIC=575.2

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-3.777574	167.8147	144.7328	-0.2736438	2.979931	0.4729445

ACF1

Training set -0.03416144

Forecasts for Time Series ID: 1003

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6693.121	6707.397	6750.804	6798.718
1992	6858.676	6918.635	6978.593	7038.551

Summary for ARIMA model of Time Series ID: 1004

Series: train\_data

ARIMA(0,1,1) with drift

Coefficients:

	ma1	drift
	-0.7081	47.9676
s.e.	0.1228	7.2280

$\sigma^2 = 23127$ : log likelihood = -276.39

AIC=558.77 AICc=559.39 BIC=564.06

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-8.889888	146.8003	105.838	-0.2744015	2.24214	0.4717803

ACF1

Training set -0.009220295

Forecasts for Time Series ID: 1004

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5943.583	5991.551	6039.519	6087.486
1992	6135.454	6183.421	6231.389	6279.357

Summary for ARIMA model of Time Series ID: 1005

Series: train\_data

ARIMA(2,1,0)(0,0,2)[4] with drift

Coefficients:

	ar1	ar2	sma1	sma2	drift
	1.0526	-0.6109	-0.2265	-0.4192	39.9323
s.e.	0.1378	0.1408	0.2012	0.1489	5.1292

$\sigma^2 = 1510$ : log likelihood = -217.64

AIC=447.27 AICc=449.6 BIC=457.84

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-1.71154	36.11749	29.85933	-0.05046774	0.6070018	0.129633
ACF1						
Training set	0.08152119					

Forecasts for Time Series ID: 1005

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5772.773	5825.686	5871.001	5905.261
1992	5941.759	6003.252	6049.594	6100.330

Summary for ARIMA model of Time Series ID: 1006

Series: train\_data

ARIMA(0,1,0)(0,0,1)[4] with drift

Coefficients:

	sma1	drift
	-0.3865	38.0903
s.e.	0.1690	10.4176

$\sigma^2 = 11076$ : log likelihood = -260.53

AIC=527.06 AICc=527.68 BIC=532.35

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-5.579311	101.5898	83.71234	-0.1943286	1.675919	0.396248
ACF1						
Training set	-0.05585935					

Forecasts for Time Series ID: 1006

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5961.932	5989.347	6101.629	6130.721
1992	6168.812	6206.902	6244.992	6283.083

Summary for ARIMA model of Time Series ID: 1007

Series: train\_data

ARIMA(0,2,1)

Coefficients:

ma1  
-0.6716  
s.e. 0.1289

$\sigma^2 = 12701$ : log likelihood = -257.83

AIC=519.65 AICc=519.96 BIC=523.13

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	8.336028	108.7886	91.86791	0.1708783	1.640634	0.2046227

ACF1

Training set -0.01489013

Forecasts for Time Series ID: 1007

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8602.890	8756.281	8909.671	9063.061
1992	9216.452	9369.842	9523.233	9676.623

Summary for ARIMA model of Time Series ID: 1008

Series: train\_data

ARIMA(3,1,0)

Coefficients:

	ar1	ar2	ar3
	0.2477	0.5048	-0.3184
s.e.	0.1479	0.1486	0.1629

$\sigma^2 = 37488$ : log likelihood = -286.32

AIC=580.65 AICc=581.7 BIC=587.69

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	31.72793	184.6088	145.7247	0.6253843	2.916929	0.2942446

ACF1

Training set -0.06306129

Forecasts for Time Series ID: 1008

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6418.820	6197.354	6342.017	6215.821
1992	6328.086	6246.143	6322.687	6264.546

Summary for ARIMA model of Time Series ID: 1009

Series: train\_data

ARIMA(0,2,1)

Coefficients:

	ma1
	-0.8892
s.e.	0.0754

sigma^2 = 18605: log likelihood = -266.32  
AIC=536.65 AICc=536.96 BIC=540.13

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	28.71826	131.6672	107.2456	0.555191	2.105124	0.3537417	-0.03056659

Forecasts for Time Series ID: 1009

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6960.367	7071.234	7182.101	7292.968
1992	7403.835	7514.702	7625.569	7736.436

Summary for ARIMA model of Time Series ID: 1010

Series: train\_data

ARIMA(1,1,0) with drift

Coefficients:

	ar1	drift
	0.3514	66.3001
s.e.	0.1455	35.8439

sigma^2 = 24840: log likelihood = -277.64  
AIC=561.28 AICc=561.9 BIC=566.56

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	1.134408	152.1383	111.4108	-0.05127389	2.356466	0.2405307
	ACF1					
Training set	-0.03397648					

Forecasts for Time Series ID: 1010

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6917.528	6954.212	7010.105	7072.747
1992	7137.762	7203.610	7269.751	7335.996

Summary for ARIMA model of Time Series ID: 1011

Series: train\_data

ARIMA(0,1,0)

$\sigma^2 = 14107$ : log likelihood = -92.94

AIC=187.88 AICc=188.19 BIC=188.59

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	36.07297	115.0021	87.13547	0.6399447	1.597507	0.5349837	-0.2580519

Forecasts for Time Series ID: 1011

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5739.5	5739.5	5739.5	5739.5
1992	5739.5	5739.5	5739.5	5739.5

Summary for ARIMA model of Time Series ID: 1012

Series: train\_data

ARIMA(1,1,0)(0,0,1)[4] with drift

Coefficients:

	ar1	sma1	drift
	-0.6300	-0.3551	52.8290
s.e.	0.1196	0.1569	20.4517

```
sigma^2 = 104501:  log likelihood = -308.4
AIC=624.8   AICc=625.85   BIC=631.84
```

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-13.61012	308.2227	236.3894	-0.7034427	4.490145	0.610175

ACF1

Training set -0.06968645

Forecasts for Time Series ID: 1012

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6634.043	6595.406	6876.293	6901.717
1992	6971.810	7013.763	7073.444	7121.957

Summary for ARIMA model of Time Series ID: 1013

Series: train\_data

ARIMA(2,2,1)

Coefficients:

	ar1	ar2	ma1
	-0.4849	-0.4083	-0.7705
s.e.	0.1537	0.1475	0.1044

```
sigma^2 = 19673:  log likelihood = -266.84
AIC=541.68   AICc=542.76   BIC=548.63
```

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	30.49079	132.052	100.062	0.5904857	1.866572	0.3282739	-0.1018717



Forecasts for Time Series ID: 1013

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7399.821	7512.016	7596.888	7693.426
1992	7795.464	7890.072	7986.037	8084.377

Summary for ARIMA model of Time Series ID: 1014

Series: train\_data

ARIMA(0,2,2)

Coefficients:

	ma1	ma2
	-1.1039	0.3653
s.e.	0.1997	0.1855

$\sigma^2 = 13147$ : log likelihood = -258.41

AIC=522.81 AICc=523.44 BIC=528.02

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	30.25781	109.3252	83.93728	0.5180617	1.623024	0.3066342

ACF1

Training set -0.04093938

Forecasts for Time Series ID: 1014

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7610.891	7882.380	8153.869	8425.358
1992	8696.847	8968.337	9239.826	9511.315

Summary for ARIMA model of Time Series ID: 1015

Series: train\_data

ARIMA(0,2,2)

Coefficients:

	ma1	ma2
	-1.1635	0.2761
s.e.	0.1587	0.1511

$\sigma^2 = 18705$ : log likelihood = -266.11

AIC=538.21 AICc=538.84 BIC=543.42

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	29.96602	130.4006	101.4565	0.589516	1.995716	0.3333411	-0.03110622

Forecasts for Time Series ID: 1015

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7178.750	7282.606	7386.463	7490.320
1992	7594.177	7698.033	7801.890	7905.747

Summary for ARIMA model of Time Series ID: 1016

Series: train\_data

ARIMA(0,2,1)

Coefficients:

	ma1
	-0.6704
s.e.	0.1601

$\sigma^2 = 43547$ : log likelihood = -283.7

AIC=571.4 AICc=571.71 BIC=574.88

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-1.402436	201.4393	144.5834	0.05395704	2.453735	0.2488954

ACF1

Training set 0.01952563

Forecasts for Time Series ID: 1016

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9161.029	9224.558	9288.086	9351.615
1992	9415.144	9478.673	9542.201	9605.730

Summary for ARIMA model of Time Series ID: 1017

Series: train\_data

ARIMA(0,2,3)

Coefficients:

	ma1	ma2	ma3
	-1.1959	0.1724	0.3253
s.e.	0.1600	0.2339	0.1480

$\sigma^2 = 12760$ : log likelihood = -257.91

AIC=523.83 AICc=524.91 BIC=530.78

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	12.95563	106.3494	83.85798	0.3205421	1.656687	0.3244179	0.01858664

Forecasts for Time Series ID: 1017

	Qtr1	Qtr2	Qtr3	Qtr4
--	------	------	------	------

1991 6643.737 6694.831 6706.303 6717.775  
1992 6729.247 6740.719 6752.192 6763.664

Summary for ARIMA model of Time Series ID: 1018

Series: train\_data

ARIMA(0,1,0)(0,0,1)[4] with drift

Coefficients:

	sma1	drift
	-0.5193	26.8908
s.e.	0.1812	12.8767

$\sigma^2 = 25506$ : log likelihood = -278.77

AIC=563.54 AICc=564.16 BIC=568.83

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-2.084417	154.1652	126.3741	-0.100059	2.61344	0.4546853	0.02342655

Forecasts for Time Series ID: 1018

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5226.554	5259.397	5383.484	5366.804
1992	5393.695	5420.586	5447.476	5474.367

Summary for ARIMA model of Time Series ID: 1019

Series: train\_data

ARIMA(0,1,0)

$\sigma^2 = 35083$ : log likelihood = -286.02

AIC=574.04 AICc=574.14 BIC=575.8

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	32.24425	185.1638	132.2215	0.5247727	2.595703	0.4864662	-0.1816933

Forecasts for Time Series ID: 1019

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6161	6161	6161	6161
1992	6161	6161	6161	6161

Summary for ARIMA model of Time Series ID: 1020

Series: train\_data

ARIMA(2,1,1) with drift

Coefficients:

	ar1	ar2	ma1	drift
	0.3794	-0.3337	0.7984	45.8223
s.e.	0.1533	0.1556	0.0826	13.1120

$\sigma^2 = 2304$ : log likelihood = -226.45

AIC=462.9 AICc=464.53 BIC=471.71

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-0.160375	45.18675	39.07145	-0.02445029	0.7717598	0.159679

ACF1

Training set 0.06658931

Forecasts for Time Series ID: 1020

	Qtr1	Qtr2	Qtr3	Qtr4
--	------	------	------	------

1991 6338.542 6415.428 6481.472 6524.599  
1992 6562.651 6606.424 6654.063 6701.258

Summary for ARIMA model of Time Series ID: 1021

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift  
57.0698  
s.e. 24.5722

$\sigma^2 = 26582$ : log likelihood = -279.55

AIC=563.1 AICc=563.4 BIC=566.62

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.09900973	159.2902	129.5197	-0.1502942	2.587729	0.3523747

ACF1

Training set 0.1975923

Forecasts for Time Series ID: 1021

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6924.570	6981.640	7038.709	7095.779
1992	7152.849	7209.919	7266.988	7324.058

Summary for ARIMA model of Time Series ID: 1022

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift  
63.1163  
s.e. 18.6335

sigma<sup>2</sup> = 15286: log likelihood = -267.65  
AIC=539.31 AICc=539.61 BIC=542.83

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.07567914	120.7926	97.31247	-0.08623549	2.283608	0.3125501

ACF1

Training set 0.1971945

Forecasts for Time Series ID: 1022

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6170.116	6233.233	6296.349	6359.465
1992	6422.581	6485.698	6548.814	6611.930

Summary for ARIMA model of Time Series ID: 1023

Series: train\_data

ARIMA(0,1,1) with drift

Coefficients:

ma1 drift  
-0.5414 130.6034  
s.e. 0.1206 7.4191

sigma<sup>2</sup> = 11152: log likelihood = -260.53  
AIC=527.06 AICc=527.67 BIC=532.34

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-1.027825	101.9386	80.11251	-0.2201263	1.62209	0.1530398

ACF1

Training set -0.04368728

Forecasts for Time Series ID: 1023

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8454.130	8584.733	8715.337	8845.940
1992	8976.544	9107.147	9237.751	9368.354

Summary for ARIMA model of Time Series ID: 1024

Series: train\_data

ARIMA(2,1,0) with drift

Coefficients:

	ar1	ar2	drift
	0.1972	0.2837	59.4453
s.e.	0.1454	0.1473	27.6363

$\sigma^2 = 10089$ : log likelihood = -257.79

AIC=523.59 AICc=524.64 BIC=530.63

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-0.4421622	95.76836	70.97219	0.01786373	2.338031	0.2161184

ACF1

Training set 0.05546528



Forecasts for Time Series ID: 1024

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4191.713	4199.432	4232.240	4271.756
1992	4319.713	4371.238	4425.862	4482.110

Summary for ARIMA model of Time Series ID: 1025

Series: train\_data

ARIMA(0,1,0)(0,0,1)[4] with drift

Coefficients:

	sma1	drift
	-0.4246	125.9893
s.e.	0.1751	21.3861

$\sigma^2 = 53019$ : log likelihood = -294.27

AIC=594.55 AICc=595.16 BIC=599.83

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-9.606145	222.2708	186.2137	-0.9578391	4.169168	0.3443937

ACF1

Training set -0.02747998

Forecasts for Time Series ID: 1025

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8183.287	8247.646	8448.793	8492.918
1992	8618.907	8744.897	8870.886	8996.875

Summary for ARIMA model of Time Series ID: 1026

Series: train\_data

ARIMA(0,1,0)(0,0,1)[4] with drift

Coefficients:

	sma1	drift
	-0.5429	134.4909
s.e.	0.2575	18.5847

sigma^2 = 54964: log likelihood = -295.35

AIC=596.7 AICc=597.31 BIC=601.98

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-7.400008	226.3101	176.4199	-0.573544	3.336576	0.2875688	0.1038798

Forecasts for Time Series ID: 1026

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8199.949	8557.742	8692.271	8963.051
1992	9097.542	9232.033	9366.524	9501.015

Summary for ARIMA model of Time Series ID: 1027

Series: train\_data

ARIMA(0,2,1)(0,0,1)[4]

Coefficients:

	ma1	sma1
	-0.5880	-0.5218
s.e.	0.1194	0.2534

sigma^2 = 5272: log likelihood = -239.45

AIC=484.91 AICc=485.54 BIC=490.12

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	5.925756	69.2288	51.64031	0.1390986	0.8523613	0.08381976
ACF1						

Training set -0.1124585

Forecasts for Time Series ID: 1027

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9648.585	9739.625	9953.397	10105.212
1992	10251.878	10398.544	10545.209	10691.875

Summary for ARIMA model of Time Series ID: 1028

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift	
	34.2535
s.e.	6.0451

$\sigma^2 = 1609$ : log likelihood = -219.25

AIC=442.5 AICc=442.8 BIC=446.02

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.08871692	39.19161	29.66007	-0.003009321	0.6356089	0.2071704
ACF1						

Training set -0.1234328

Forecasts for Time Series ID: 1028

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5444.953	5479.207	5513.460	5547.714
1992	5581.967	5616.221	5650.474	5684.728

Summary for ARIMA model of Time Series ID: 1029

Series: train\_data

ARIMA(0,1,1)(0,0,1)[4] with drift

Coefficients:

	ma1	sma1	drift
	-0.5317	-0.3712	58.4123
s.e.	0.1191	0.1953	5.4719

$\sigma^2 = 13243$ : log likelihood = -264.01

AIC=536.02 AICc=537.08 BIC=543.07

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-1.4582	109.7227	89.16849	-0.07457864	1.368103	0.3391565

ACF1

Training set -0.05974379

Forecasts for Time Series ID: 1029

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7994.186	7986.191	8145.252	8187.925
1992	8238.434	8296.847	8355.259	8413.671

Summary for ARIMA model of Time Series ID: 1030

Series: train\_data

ARIMA(0,1,0)(2,0,1)[4] with drift

Coefficients:

	sar1	sar2	sma1	drift
	0.1609	-0.4500	-0.5228	25.7383
s.e.	0.2301	0.1576	0.2413	6.9896

sigma^2 = 11359: log likelihood = -261.4

AIC=532.79 AICc=534.42 BIC=541.6

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.3749715	100.3386	75.37939	-0.0441398	1.959546	0.2600186

ACF1

Training set 0.1810952

Forecasts for Time Series ID: 1030

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4075.200	4181.230	4209.971	4361.282
1992	4358.938	4513.409	4557.154	4668.775

Summary for ARIMA model of Time Series ID: 1031

Series: train\_data

ARIMA(0,1,0)(1,0,0)[4] with drift

Coefficients:

	sar1	drift
	-0.3220	80.1032
s.e.	0.1434	26.6991

```
sigma^2 = 53621:  log likelihood = -294.34
AIC=594.68  AICc=595.29  BIC=599.96
```

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-4.141351	223.5295	175.8924	-0.3370834	3.149706	0.3861313
ACF1						

Training set -0.1491866

Forecasts for Time Series ID: 1031

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8171.936	8225.184	8300.652	8326.850
1992	8426.489	8515.240	8596.836	8694.297

Summary for ARIMA model of Time Series ID: 1032

Series: train\_data

ARIMA(3,1,0)

Coefficients:

	ar1	ar2	ar3
	0.2477	0.5049	-0.3184
s.e.	0.1479	0.1486	0.1630

```
sigma^2 = 59112:  log likelihood = -296.12
AIC=600.23  AICc=601.28  BIC=607.28
```

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	39.8385	231.814	182.9496	0.6253116	2.915743	0.2941489	-0.06313375

Forecasts for Time Series ID: 1032

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8061.399	7783.052	7964.868	7806.198
1992	7947.313	7844.269	7940.511	7867.395

Summary for ARIMA model of Time Series ID: 1033

Series: train\_data

ARIMA(0,1,0)(0,0,1)[4] with drift

Coefficients:

	sma1	drift
	-0.3303	62.7418
s.e.	0.1773	8.5625

$\sigma^2 = 6540$ : log likelihood = -249.11

AIC=504.22 AICc=504.84 BIC=509.5

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-0.5302771	78.0646	64.82659	-0.02958115	0.8345742	0.2329378

ACF1

Training set 0.1414672

Forecasts for Time Series ID: 1033

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9275.328	9347.047	9460.370	9544.838
1992	9607.580	9670.322	9733.063	9795.805

Summary for ARIMA model of Time Series ID: 1034

Series: train\_data

ARIMA(1,1,0) with drift

Coefficients:

	ar1	drift
	-0.3061	63.9036
s.e.	0.1468	4.5796

$\sigma^2 = 1594$ : log likelihood = -218.58

AIC=443.16 AICc=443.78 BIC=448.44

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-0.2603967	38.54157	32.18771	0.02550812	0.8616422	0.1268794

ACF1

Training set 0.05804836

Forecasts for Time Series ID: 1034

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5319.874	5381.491	5446.094	5509.783
1992	5573.753	5637.636	5701.546	5765.447

Summary for ARIMA model of Time Series ID: 1035

Series: train\_data

ARIMA(1,1,0) with drift

Coefficients:

	ar1	drift
	0.3809	63.6306
s.e.	0.1393	7.9356



sigma^2 = 1118: log likelihood = -210.98  
AIC=427.97 AICc=428.58 BIC=433.25

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.2286188	32.27915	23.72794	0.01258423	0.6368267	0.08951829
ACF1						

Training set -0.06664814

Forecasts for Time Series ID: 1035

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5125.914	5186.986	5249.642	5312.902
1992	5376.391	5439.968	5503.578	5567.201

Summary for ARIMA model of Time Series ID: 1036

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift  
45.6744  
s.e. 14.1718

sigma^2 = 8842: log likelihood = -255.88  
AIC=515.77 AICc=516.07 BIC=519.29

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.06789373	91.86964	70.20584	-0.0334733	1.724436	0.3384026
ACF1						

Training set 0.04289913

Forecasts for Time Series ID: 1036

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5042.674	5088.349	5134.023	5179.698
1992	5225.372	5271.047	5316.721	5362.395

Summary for ARIMA model of Time Series ID: 1037

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift
53.2907
s.e. 21.3039

$\sigma^2 = 19981$ : log likelihood = -273.41

AIC=550.82 AICc=551.12 BIC=554.35

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.06602745	138.1031	97.32818	-0.02552952	2.198919	0.3513653

ACF1

Training set 0.04782918

Forecasts for Time Series ID: 1037

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5303.291	5356.581	5409.872	5463.163
1992	5516.453	5569.744	5623.035	5676.326

Summary for ARIMA model of Time Series ID: 1038

Series: train\_data

ARIMA(0,2,1)(0,0,1)[4]

Coefficients:

	ma1	sma1
	-0.6450	-0.4471
s.e.	0.1527	0.1660

$\sigma^2 = 1653$ : log likelihood = -214.98

AIC=435.95 AICc=436.59 BIC=441.17

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	2.284332	38.76018	27.38028	0.06819027	0.9079859	0.08923163
ACF1						
Training set	0.00201347					

Forecasts for Time Series ID: 1038

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4902.752	4957.846	5068.902	5163.734
1992	5247.777	5331.820	5415.863	5499.906

Summary for ARIMA model of Time Series ID: 1039

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift
112.5395

s.e. 16.9446

$\sigma^2 = 12640$ : log likelihood = -263.57

AIC=531.14 AICc=531.44 BIC=534.66

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.05085135	109.8439	87.08764	-0.2795087	2.120308	0.1852101
ACF1						

Training set 0.120956

Forecasts for Time Series ID: 1039

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7301.740	7414.279	7526.819	7639.358
1992	7751.898	7864.437	7976.977	8089.516

Summary for ARIMA model of Time Series ID: 1040

Series: train\_data

ARIMA(0,1,1) with drift

Coefficients:

	ma1	drift
	-0.2848	89.5719
s.e.	0.1664	15.3265

$\sigma^2 = 20119$ : log likelihood = -273.08

AIC=552.17 AICc=552.78 BIC=557.45

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
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Training set -1.439028 136.919 103.322 -0.4107154 2.948882 0.2650386 0.02422386

Forecasts for Time Series ID: 1040

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5665.658	5755.229	5844.801	5934.373
1992	6023.945	6113.517	6203.089	6292.661

Summary for ARIMA model of Time Series ID: 1041

Series: train\_data

ARIMA(0,2,1)(0,0,1)[4]

Coefficients:

	ma1	sma1
	-0.5880	-0.5218
s.e.	0.1194	0.2534

$\sigma^2 = 5272$ : log likelihood = -239.45

AIC=484.91 AICc=485.54 BIC=490.12

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	5.925756	69.2288	51.64031	0.1390986	0.8523613	0.08381976

ACF1

Training set -0.1124585

Forecasts for Time Series ID: 1041

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9648.585	9739.625	9953.397	10105.212
1992	10251.878	10398.544	10545.209	10691.875

Summary for ARIMA model of Time Series ID: 1042

Series: train\_data

ARIMA(0,1,0)

$\sigma^2 = 212232$ : log likelihood = -324.72

AIC=651.44 AICc=651.54 BIC=653.2

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	47.35395	455.4216	262.7176	0.5147982	5.554388	0.4001791	-0.1424063

Forecasts for Time Series ID: 1042

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5654	5654	5654	5654
1992	5654	5654	5654	5654

Summary for ARIMA model of Time Series ID: 1043

Series: train\_data

ARIMA(0,2,1)

Coefficients:

ma1	
	-0.6939
s.e.	0.1405

$\sigma^2 = 4903$ : log likelihood = -237.86

AIC=479.73 AICc=480.04 BIC=483.2

Training set error measures:

ME	RMSE	MAE	MPE	MAPE	MASE
----	------	-----	-----	------	------

Training set 2.15914 67.58971 51.57152 0.0871844 0.8848716 0.0856147

ACF1

Training set -0.004330942

Forecasts for Time Series ID: 1043

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9385.632	9506.364	9627.096	9747.828
1992	9868.561	9989.293	10110.025	10230.757

Summary for ARIMA model of Time Series ID: 1044

Series: train\_data

ARIMA(0,2,1)(0,0,1)[4]

Coefficients:

	ma1	sma1
	-0.5880	-0.5218
s.e.	0.1194	0.2534

$\sigma^2 = 5272$ : log likelihood = -239.45

AIC=484.91 AICc=485.54 BIC=490.12

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	5.925756	69.2288	51.64031	0.1390986	0.8523613	0.08381976

ACF1

Training set -0.1124585

Forecasts for Time Series ID: 1044

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9648.585	9739.625	9953.397	10105.212

1992 10251.878 10398.544 10545.209 10691.875

Summary for ARIMA model of Time Series ID: 1045

Series: train\_data

ARIMA(0,1,0)(1,0,0)[4]

Coefficients:

        sar1  
        -0.4692  
s.e.    0.1280

sigma^2 = 204798: log likelihood = -323.95

AIC=651.89 AICc=652.19 BIC=655.41

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	63.75348	442.141	265.5665	0.6787665	4.498399	0.377923	-0.1154057

Forecasts for Time Series ID: 1045

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7230.163	7239.547	7178.553	7082.839
1992	7126.866	7122.463	7151.081	7195.988

Summary for ARIMA model of Time Series ID: 1046

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

        drift  
        58.5628



s.e. 11.5963

$\sigma^2 = 5921$ : log likelihood = -247.26

AIC=498.52 AICc=498.82 BIC=502.04

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.1429894	75.17865	63.3376	-0.008959971	0.8405378	0.2466417
ACF1						

Training set 0.1840323

Forecasts for Time Series ID: 1046

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8926.863	8985.426	9043.988	9102.551
1992	9161.114	9219.677	9278.240	9336.802

Summary for ARIMA model of Time Series ID: 1047

Series: train\_data

ARIMA(0,1,0)(0,0,1)[4] with drift

Coefficients:

	sma1	drift
	-0.3303	62.7418
s.e.	0.1773	8.5625

$\sigma^2 = 6540$ : log likelihood = -249.11

AIC=504.22 AICc=504.84 BIC=509.5

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
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Training set -0.5302771 78.0646 64.82659 -0.02958115 0.8345742 0.2329378

ACF1

Training set 0.1414672

Forecasts for Time Series ID: 1047

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9275.328	9347.047	9460.370	9544.838
1992	9607.580	9670.322	9733.063	9795.805

Summary for ARIMA model of Time Series ID: 1048

Series: train\_data

ARIMA(0,2,0)(0,0,1)[4]

Coefficients:

sma1  
-0.4750  
s.e. 0.1875

$\sigma^2 = 491.6$ : log likelihood = -189.74

AIC=383.48 AICc=383.79 BIC=386.96

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.8452872	21.40274	15.68487	0.03534527	0.3414403	0.0335335

ACF1

Training set 0.09859012

Forecasts for Time Series ID: 1048

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7339.968	7449.473	7555.190	7661.152

1992 7767.115 7873.078 7979.041 8085.003

Summary for ARIMA model of Time Series ID: 1049

Series: train\_data

ARIMA(2,0,0)(2,1,0)[4]

Coefficients:

	ar1	ar2	sar1	sar2
	1.4031	-0.4443	-0.9947	-0.5872
s.e.	0.1616	0.1596	0.1387	0.1274

$\sigma^2 = 23792$ : log likelihood = -259.78

AIC=529.57 AICc=531.33 BIC=538.01

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	19.53409	139.5198	108.5423	0.9812794	4.679077	0.3441908	-0.0568332

Forecasts for Time Series ID: 1049

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3173.379	3027.413	3663.011	4232.519
1992	3525.396	3340.667	3740.827	4100.521

Summary for ARIMA model of Time Series ID: 1050

Series: train\_data

ARIMA(1,1,0)(0,0,1)[4] with drift

Coefficients:

	ar1	sma1	drift
	-0.2745	0.3009	50.8185

s.e. 0.1542 0.1581 25.1775

$\sigma^2 = 28913$ : log likelihood = -280.54

AIC=569.08 AICc=570.13 BIC=576.12

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.9164337	162.1265	119.1677	-0.02402529	3.823502	0.3793943

ACF1

Training set -0.0009110078

Forecasts for Time Series ID: 1050

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4170.698	4191.026	4224.506	4182.610
1992	4258.878	4302.711	4355.447	4405.739

Summary for ARIMA model of Time Series ID: 1051

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift

57.7767

s.e. 16.1704

$\sigma^2 = 11511$ : log likelihood = -261.56

AIC=527.11 AICc=527.41 BIC=530.64

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
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Training set 0.02830961 104.8248 76.44247 -0.0614075 2.840399 0.2427477

ACF1

Training set 0.2252838

Forecasts for Time Series ID: 1051

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3845.577	3903.353	3961.130	4018.907
1992	4076.684	4134.460	4192.237	4250.014

Summary for ARIMA model of Time Series ID: 1052

Series: train\_data

ARIMA(2,1,0) with drift

Coefficients:

	ar1	ar2	drift
	0.1972	0.2837	59.4453
s.e.	0.1454	0.1473	27.6363

$\sigma^2 = 10089$ : log likelihood = -257.79

AIC=523.59 AICc=524.64 BIC=530.63

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-0.4421622	95.76836	70.97219	0.01786373	2.338031	0.2161184

ACF1

Training set 0.05546528

Forecasts for Time Series ID: 1052

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4191.713	4199.432	4232.240	4271.756

1992 4319.713 4371.238 4425.862 4482.110

Summary for ARIMA model of Time Series ID: 1053

Series: train\_data

ARIMA(0,1,3) with drift

Coefficients:

	ma1	ma2	ma3	drift
	0.2667	0.5529	0.5671	65.2721
s.e.	0.1304	0.1024	0.1253	38.6428

$\sigma^2 = 13148$ : log likelihood = -263.84

AIC=537.67 AICc=539.29 BIC=546.48

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-2.410205	107.9546	78.48924	-0.100184	2.820853	0.1888917
ACF1						

Training set 0.09853504

Forecasts for Time Series ID: 1053

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4407.464	4421.851	4415.620	4480.892
1992	4546.164	4611.436	4676.708	4741.980

Summary for ARIMA model of Time Series ID: 1054

Series: train\_data

ARIMA(0,1,1) with drift

Coefficients:

	ma1	drift
	0.5320	135.0805
s.e.	0.1876	63.8239

sigma^2 = 79316: log likelihood = -302.7  
AIC=611.4 AICc=612.02 BIC=616.69

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.9926209	271.8606	202.2466	-0.2244582	4.54793	0.2525873

ACF1  
Training set -0.07402446

Forecasts for Time Series ID: 1054

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7652.834	7787.915	7922.995	8058.076
1992	8193.157	8328.237	8463.318	8598.398

Summary for ARIMA model of Time Series ID: 1055

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

	drift
	96.0233
s.e.	41.8722

sigma^2 = 77186: log likelihood = -302.47  
AIC=608.94 AICc=609.24 BIC=612.46

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.05163581	271.4363	203.4872	-0.04806934	4.168812	0.338581

ACF1

Training set 0.01781899

Forecasts for Time Series ID: 1055

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6593.023	6689.047	6785.070	6881.093
1992	6977.116	7073.140	7169.163	7265.186

Summary for ARIMA model of Time Series ID: 1056

Series: train\_data

ARIMA(1,1,0)(0,0,1)[4]

Coefficients:

	ar1	sma1
	0.6211	-0.4253
s.e.	0.1266	0.1736

$\sigma^2 = 152028$ : log likelihood = -317.1

AIC=640.2 AICc=640.82 BIC=645.49

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	67.83083	376.3808	239.4053	1.745091	5.009403	0.2262542	-0.04616856

Forecasts for Time Series ID: 1056

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5891.573	5893.367	6207.715	6234.560



1992 6251.235 6261.592 6268.024 6272.020

Summary for ARIMA model of Time Series ID: 1057

Series: train\_data

ARIMA(2,1,0)

Coefficients:

	ar1	ar2
	0.4165	0.3075
s.e.	0.1418	0.1440

$\sigma^2 = 39024$ : log likelihood = -287.61

AIC=581.22 AICc=581.84 BIC=586.51

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	29.74294	190.6926	154.8829	0.7112113	2.963211	0.2096979

ACF1

Training set 0.002323646

Forecasts for Time Series ID: 1057

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7871.843	7811.325	7765.618	7727.968
1992	7698.229	7674.263	7655.135	7639.797

Summary for ARIMA model of Time Series ID: 1058

Series: train\_data

ARIMA(0,1,0)

$\sigma^2 = 47532$ : log likelihood = -292.55

AIC=587.1    AICc=587.2    BIC=588.86

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	5.856591	215.5261	164.9475	-0.006475213	4.251634	0.5993732

ACF1

Training set -0.3069186

Forecasts for Time Series ID: 1058

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3944	3944	3944	3944
1992	3944	3944	3944	3944

Summary for ARIMA model of Time Series ID: 1059

Series: train\_data

ARIMA(0,1,0)

$\sigma^2 = 15843$ : log likelihood = -268.93

AIC=539.86    AICc=539.96    BIC=541.62

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	20.61896	124.4323	99.21896	0.5686739	2.871105	0.3343971	0.20434

Forecasts for Time Series ID: 1059

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3738.8	3738.8	3738.8	3738.8
1992	3738.8	3738.8	3738.8	3738.8

Summary for ARIMA model of Time Series ID: 1060

Series: train\_data

ARIMA(0,1,0)(2,0,1)[4] with drift

Coefficients:

	sar1	sar2	sma1	drift
	0.1609	-0.4500	-0.5228	25.7383
s.e.	0.2301	0.1576	0.2413	6.9896

$\sigma^2 = 11359$ : log likelihood = -261.4

AIC=532.79 AICc=534.42 BIC=541.6

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.3749715	100.3386	75.37939	-0.0441398	1.959546	0.2600186

ACF1

Training set 0.1810952

Forecasts for Time Series ID: 1060

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4075.200	4181.230	4209.971	4361.282
1992	4358.938	4513.409	4557.154	4668.775

Summary for ARIMA model of Time Series ID: 1061

Series: train\_data

ARIMA(2,0,1) with non-zero mean

Coefficients:

	ar1	ar2	ma1	mean
	1.7525	-0.8611	-0.5976	4139.280
s.e.	0.0996	0.0897	0.1640	90.236

sigma^2 = 25806: log likelihood = -285.14

AIC=580.27 AICc=581.85 BIC=589.19

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	4.330899	153.1657	124.2396	-0.03522399	2.958577	0.2609254

ACF1

Training set -0.04399749

Forecasts for Time Series ID: 1061

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4093.760	3996.891	3928.940	3893.268
1992	3889.260	3912.953	3957.925	4016.338

Summary for ARIMA model of Time Series ID: 1062

Series: train\_data

ARIMA(0,1,1)

Coefficients:

ma1
0.4351
s.e. 0.1895

sigma^2 = 114886: log likelihood = -311.12

AIC=626.25 AICc=626.55 BIC=629.77

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	57.38214	331.1554	254.7715	0.9726094	4.417362	0.3322529

ACF1

Training set -0.08880246

Forecasts for Time Series ID: 1062

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7393.124	7393.124	7393.124	7393.124
1992	7393.124	7393.124	7393.124	7393.124

Summary for ARIMA model of Time Series ID: 1063

Series: train\_data

ARIMA(0,1,0)

$\sigma^2 = 115327$ : log likelihood = -311.61

AIC=625.22 AICc=625.31 BIC=626.98

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	47.12059	335.7166	254.3479	0.7311856	4.384744	0.3790156

ACF1

Training set 0.003645485

Forecasts for Time Series ID: 1063

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6375	6375	6375	6375
1992	6375	6375	6375	6375

Summary for ARIMA model of Time Series ID: 1064

Series: train\_data

ARIMA(1,1,0)

Coefficients:

ar1  
0.3689  
s.e. 0.1400

sigma<sup>2</sup> = 211529: log likelihood = -324.22  
AIC=652.43 AICc=652.73 BIC=655.96

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	12.80561	449.348	356.5387	0.1177785	5.150877	0.3348567	-0.02848343

Forecasts for Time Series ID: 1064

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7055.048	7067.978	7072.749	7074.509
1992	7075.158	7075.397	7075.486	7075.518

Summary for ARIMA model of Time Series ID: 1065

Series: train\_data

ARIMA(2,1,0)

Coefficients:

ar1 ar2  
0.2748 0.3200  
s.e. 0.1417 0.1466

sigma<sup>2</sup> = 63569: log likelihood = -297.97  
AIC=601.95 AICc=602.56 BIC=607.23

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	16.29104	243.3817	201.3774	0.2699221	2.835663	0.2740481	0.04599345

Forecasts for Time Series ID: 1065

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7812.905	7752.765	7722.288	7694.668
1992	7677.326	7663.722	7654.435	7647.529

Summary for ARIMA model of Time Series ID: 1066

Series: train\_data

ARIMA(0,2,1)(0,0,1)[4]

Coefficients:

	ma1	sma1
	-0.7099	-0.5579
s.e.	0.1177	0.1273

$\sigma^2 = 1215$ : log likelihood = -208.97

AIC=423.94 AICc=424.57 BIC=429.15

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	4.641493	33.2353	25.10756	0.0875314	0.6644132	0.07209637

ACF1

Training set -0.05017086

Forecasts for Time Series ID: 1066

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6064.453	6165.792	6273.159	6376.772
1992	6478.981	6581.189	6683.398	6785.607

Summary for ARIMA model of Time Series ID: 1067

Series: train\_data

ARIMA(1,1,0)(0,0,1)[4] with drift

Coefficients:

	ar1	sma1	drift
	-0.4827	0.3818	86.1558
s.e.	0.1337	0.1587	12.9110

$\sigma^2 = 9190$ : log likelihood = -256.13

AIC=520.27 AICc=521.32 BIC=527.31

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.2717088	91.4019	66.306	0.02147527	1.429955	0.1859394	-0.02908334

Forecasts for Time Series ID: 1067

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6428.531	6547.250	6576.633	6676.281
1992	6755.924	6845.224	6929.862	7016.750

Summary for ARIMA model of Time Series ID: 1068

Series: train\_data

ARIMA(0,2,1)

Coefficients:

	ma1
	-0.8739
s.e.	0.0708



sigma^2 = 15502: log likelihood = -262.43

AIC=528.87 AICc=529.17 BIC=532.34

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	23.76875	120.1861	80.3627	0.4155581	1.516334	0.1440902

ACF1

Training set -0.001827488

Forecasts for Time Series ID: 1068

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9009.495	9209.989	9410.484	9610.979
1992	9811.473	10011.968	10212.462	10412.957

Summary for ARIMA model of Time Series ID: 1069

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift
102.3256
s.e. 15.5699

sigma^2 = 10673: log likelihood = -259.93

AIC=523.86 AICc=524.16 BIC=527.38

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.06135621	100.9328	73.88799	0.03715953	1.38032	0.1628206

ACF1

Training set 0.07773858

Forecasts for Time Series ID: 1069

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7304.326	7406.651	7508.977	7611.302
1992	7713.628	7815.953	7918.279	8020.605

Summary for ARIMA model of Time Series ID: 1070

Series: train\_data

ARIMA(0,2,1)

Coefficients:

	ma1
	-0.7160
s.e.	0.0993

$\sigma^2 = 2346$ : log likelihood = -222.41

AIC=448.83 AICc=449.14 BIC=452.3

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	6.964559	46.75264	39.14209	0.1927596	0.7713281	0.06416735

ACF1

Training set -0.112275

Forecasts for Time Series ID: 1070

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9055.595	9217.191	9378.786	9540.381
1992	9701.977	9863.572	10025.167	10186.763

Summary for ARIMA model of Time Series ID: 1071

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift

21.8000

s.e. 10.1913

$\sigma^2 = 2706$ : log likelihood = -133.75

AIC=271.5 AICc=272.04 BIC=273.93

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.1993537	49.97725	43.0532	0.001073569	0.7827997	0.3853419

ACF1

Training set 0.1577951

Forecasts for Time Series ID: 1071

	Qtr1	Qtr2	Qtr3	Qtr4
1992		5771.8	5793.6	
1993	5815.4	5837.2	5859.0	5880.8
1994	5902.6	5924.4		

Summary for ARIMA model of Time Series ID: 1072

Series: train\_data

ARIMA(2,0,0) with non-zero mean

Coefficients:

	ar1	ar2	mean
	0.3143	0.3729	6269.8971
s.e.	0.1874	0.1966	84.7186

sigma^2 = 20725: log likelihood = -164.8  
AIC=337.6 AICc=339.51 BIC=342.64

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	13.35221	135.403	100.4832	0.1679609	1.585759	0.6363358	-0.07304144

Forecasts for Time Series ID: 1072

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6167.164	6184.694	6204.808	6217.667
1992	6229.209	6237.632	6244.583	6249.909

Summary for ARIMA model of Time Series ID: 1073

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift	
	68.560
s.e.	40.304

sigma^2 = 42304: log likelihood = -168.12  
AIC=340.24 AICc=340.79 BIC=342.68

Training set error measures:

ME	RMSE	MAE	MPE	MAPE	MASE
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Training set 0.2404399 197.6101 144.1666 -0.03475915 2.054241 0.3670909

ACF1

Training set -0.08930591

Forecasts for Time Series ID: 1073

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8102.56	8171.12	8239.68	8308.24
1992	8376.80	8445.36	8513.92	8582.48

Summary for ARIMA model of Time Series ID: 1074

Series: train\_data

ARIMA(0,1,0)

$\sigma^2 = 19785$ : log likelihood = -159.13

AIC=320.26 AICc=320.44 BIC=321.48

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	37.85038	137.9288	113.6965	0.5539715	1.668428	0.3936613	0.08651245

Forecasts for Time Series ID: 1074

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7088	7088	7088	7088
1992	7088	7088	7088	7088

Summary for ARIMA model of Time Series ID: 1075

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift  
86.5600  
s.e. 12.3227

sigma^2 = 3956: log likelihood = -138.5  
AIC=280.99 AICc=281.54 BIC=283.43

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.2379976	60.42922	49.66877	0.01494075	0.6603715	0.1349861

ACF1  
Training set -0.1305874

Forecasts for Time Series ID: 1075

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8525.06	8611.62	8698.18	8784.74
1992	8871.30	8957.86	9044.42	9130.98

Summary for ARIMA model of Time Series ID: 1076

Series: train\_data

ARIMA(0,1,0) with drift

Coefficients:

drift  
34.2535  
s.e. 6.0451

sigma^2 = 1609: log likelihood = -219.25  
AIC=442.5 AICc=442.8 BIC=446.02

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.08871692	39.19161	29.66007	-0.003009321	0.6356089	0.2071704

ACF1

Training set -0.1234328

Forecasts for Time Series ID: 1076

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5444.953	5479.207	5513.460	5547.714
1992	5581.967	5616.221	5650.474	5684.728

Summary for ARIMA model of Time Series ID: 1077

Series: train\_data

ARIMA(1,0,0)(0,1,0)[4] with drift

Coefficients:

	ar1	drift
	0.6293	56.5057
s.e.	0.1233	5.6281

$\sigma^2 = 3177$ : log likelihood = -217.26

AIC=440.51 AICc=441.18 BIC=445.58

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	1.237832	52.38382	39.40253	-0.01378013	0.991822	0.1757476

ACF1

Training set 0.01078143

Forecasts for Time Series ID: 1077

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4886.618	5165.435	5260.851	5745.194
1992	5121.974	5397.330	5490.569	5973.542

Summary for ARIMA model of Time Series ID: 1078

Series: train\_data

ARIMA(1,0,0)(0,1,1)[4] with drift

Coefficients:

	ar1	sma1	drift
	0.7926	-0.3961	89.6647
s.e.	0.1009	0.1606	7.2435

$\sigma^2 = 4277$ : log likelihood = -223.07

AIC=454.15 AICc=455.29 BIC=460.9

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-1.193885	59.96901	44.74278	-0.01120508	0.6979053	0.1267223

ACF1

Training set -0.09605884

Forecasts for Time Series ID: 1078

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8684.741	8212.342	8412.405	8176.081
1992	9043.338	8570.951	8771.025	8534.709

Summary for ARIMA model of Time Series ID: 1079

Series: train\_data

ARIMA(0,1,1)(1,1,0)[4]



Coefficients:

	ma1	sar1
	-0.5373	-0.4280
s.e.	0.1228	0.1742

$\sigma^2 = 17653$ : log likelihood = -245.6

AIC=497.21 AICc=497.9 BIC=502.2

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	26.78473	121.8397	96.76287	0.2777864	2.443844	0.3879904	-0.1585677

Forecasts for Time Series ID: 1079

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4398.539	6167.172	6701.713	6852.954
1992	4831.652	6642.279	7237.213	7338.255

Summary for ARIMA model of Time Series ID: 1080

Series: train\_data

ARIMA(1,0,0)(2,1,0)[4] with drift

Coefficients:

	ar1	sar1	sar2	drift
	0.8775	-0.3738	-0.3784	48.5984
s.e.	0.0872	0.1500	0.1402	15.5923

$\sigma^2 = 9262$ : log likelihood = -238.53

AIC=487.05 AICc=488.81 BIC=495.49

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	2.509564	87.05148	60.09878	-0.06274081	2.258014	0.2872894

ACF1

Training set -0.04497418

Forecasts for Time Series ID: 1080

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3892.836	3840.710	4068.763	3971.471
1992	4171.623	4118.199	4309.794	4166.788

Summary for ARIMA model of Time Series ID: 1081

Series: train\_data

ARIMA(1,0,0)(0,1,1)[4] with drift

Coefficients:

	ar1	sma1	drift
	0.8793	-0.6504	39.3259
s.e.	0.0835	0.2588	11.1832

$\sigma^2 = 9990$ : log likelihood = -240.73

AIC=489.47 AICc=490.61 BIC=496.22

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	1.354891	91.65442	71.56327	-0.1470016	2.710709	0.3393449	0.1390344

Forecasts for Time Series ID: 1081

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3579.665	3712.560	3763.387	3820.286

1992 3724.907 3859.256 3911.364 3969.388

Summary for ARIMA model of Time Series ID: 1082

Series: train\_data

ARIMA(1,1,0)(1,1,0)[4]

Coefficients:

	ar1	sar1
	-0.4331	-0.3815
s.e.	0.1443	0.1727

$\sigma^2 = 2007$ : log likelihood = -203

AIC=411.99 AICc=412.68 BIC=416.99

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	8.376976	41.08341	29.93077	0.1913548	0.862694	0.1489716

ACF1

Training set -0.06714039

Forecasts for Time Series ID: 1082

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4474.509	4785.268	4939.125	5166.557
1992	4793.598	5115.951	5286.908	5504.979

Summary for ARIMA model of Time Series ID: 1083

Series: train\_data

ARIMA(0,1,1)(0,1,1)[4]

Coefficients:

	ma1	sma1
	-0.2909	-0.7307
s.e.	0.1801	0.1488

sigma^2 = 2655: log likelihood = -209.62  
AIC=425.24 AICc=425.92 BIC=430.23

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	10.75941	47.25405	36.54225	0.2890071	1.018	0.3831107	-0.02152351

Forecasts for Time Series ID: 1083

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3912.191	4160.919	4286.876	4654.404
1992	4024.629	4273.357	4399.314	4766.841

Summary for ARIMA model of Time Series ID: 1084

Series: train\_data

ARIMA(0,1,0)(1,1,0)[4]

Coefficients:

	sar1
	-0.2494
s.e.	0.1602

sigma^2 = 1474: log likelihood = -197.18  
AIC=398.36 AICc=398.7 BIC=401.69

Training set error measures:

ME	RMSE	MAE	MPE	MAPE	MASE
----	------	-----	-----	------	------

Training set 0.8047361 35.68096 22.38547 0.0120761 0.3864765 0.2902586

ACF1

Training set -0.1633188

Forecasts for Time Series ID: 1084

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6028.055	6128.038	6192.716	6293.975
1992	6126.821	6224.938	6292.789	6395.031

Summary for ARIMA model of Time Series ID: 1085

Series: train\_data

ARIMA(1,1,0)(0,1,1)[4]

Coefficients:

	ar1	sma1
	-0.4365	-0.5670
s.e.	0.1443	0.1215

$\sigma^2 = 13416$ : log likelihood = -240.5

AIC=487 AICc=487.69 BIC=491.99

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	24.09595	106.216	83.2412	0.5147804	2.255255	0.4890177	-0.1186638

Forecasts for Time Series ID: 1085

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3587.587	4949.046	5467.439	5520.183
1992	3831.413	5198.615	5714.501	5768.339

Summary for ARIMA model of Time Series ID: 1086

Series: train\_data

ARIMA(1,1,0)(0,1,1)[4]

Coefficients:

	ar1	sma1
	-0.3330	-0.6018
s.e.	0.1557	0.1507

$\sigma^2 = 41027$ : log likelihood = -262.39

AIC=530.78 AICc=531.47 BIC=535.77

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	31.56133	185.741	140.7699	0.4307771	2.220954	0.3892233	0.04387432

Forecasts for Time Series ID: 1086

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8617.452	8812.338	9287.481	9039.941
1992	9224.233	9401.524	9882.526	9633.034

Summary for ARIMA model of Time Series ID: 1087

Series: train\_data

ARIMA(0,1,0)(1,1,0)[4]

Coefficients:

	sar1
	-0.4177
s.e.	0.1431

sigma^2 = 6914: log likelihood = -227.62  
AIC=459.24 AICc=459.57 BIC=462.57

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	10.68297	77.27582	57.51375	0.3924593	2.255455	0.3745824
ACF1						

Training set -0.02213486

Forecasts for Time Series ID: 1087

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3450.627	3635.799	3612.158	3837.270
1992	3714.890	3886.405	3887.729	4109.811

Summary for ARIMA model of Time Series ID: 1088

Series: train\_data

ARIMA(0,1,0)(0,1,1)[4]

Coefficients:

sma1  
-0.2904  
s.e. 0.1727

sigma^2 = 3682: log likelihood = -215.1  
AIC=434.21 AICc=434.54 BIC=437.53

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	11.32993	56.39193	44.63695	0.1752162	0.7111207	0.3059641
ACF1						

Training set -0.1729384

Forecasts for Time Series ID: 1088

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6962.878	7426.543	7711.523	8066.145
1992	7256.743	7720.409	8005.389	8360.011

Summary for ARIMA model of Time Series ID: 1089

Series: train\_data

ARIMA(0,1,0)(1,1,0)[4]

Coefficients:

    sar1  
    -0.2938  
s.e.    0.1490

$\sigma^2 = 1242$ : log likelihood = -193.91

AIC=391.83    AICc=392.16    BIC=395.15

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-3.8761	32.75408	23.66324	-0.08352343	0.4398888	0.1319849

ACF1

Training set 0.06447286

Forecasts for Time Series ID: 1089

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6198.969	6263.341	6216.085	6259.034
1992	6398.572	6460.484	6415.213	6460.233



Summary for ARIMA model of Time Series ID: 1090

Series: train\_data

ARIMA(1,0,0)(0,1,0)[4] with drift

Coefficients:

	ar1	drift
	0.5873	61.1968
s.e.	0.1297	5.3169

$\sigma^2 = 3436$ : log likelihood = -218.77

AIC=443.55 AICc=444.21 BIC=448.61

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-1.544765	54.47237	39.79136	-0.03029638	0.7118339	0.1656593
ACF1						
Training set	0.04393093					

Forecasts for Time Series ID: 1090

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7270.952	6758.932	6862.483	6558.752
1992	7517.187	7004.569	7107.770	6803.832

Summary for ARIMA model of Time Series ID: 1091

Series: train\_data

ARIMA(1,1,0)(0,1,1)[4]

Coefficients:

	ar1	sma1
	-0.465	-0.5185

s.e. 0.141 0.1636

sigma^2 = 1864: log likelihood = -201.86

AIC=409.72 AICc=410.4 BIC=414.71

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-6.512417	39.59141	27.25695	-0.1347754	0.5118123	0.1564132

ACF1

Training set -0.02467183

Forecasts for Time Series ID: 1091

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6076.443	6239.913	6212.316	6210.405
1992	6250.527	6412.286	6385.485	6383.204

Summary for ARIMA model of Time Series ID: 1092

Series: train\_data

ARIMA(0,1,0)(0,1,1)[4]

Coefficients:

    sma1  
    -0.4213  
s.e. 0.1357

sigma^2 = 4825: log likelihood = -220.6

AIC=445.21 AICc=445.54 BIC=448.54

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
--	----	------	-----	-----	------	------

Training set -7.263373 64.55294 50.62336 -0.1479364 0.9754055 0.3715476

ACF1

Training set -0.0514616

Forecasts for Time Series ID: 1092

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5666.657	5488.509	5522.482	5497.280
1992	5727.438	5549.290	5583.262	5558.061

Summary for ARIMA model of Time Series ID: 1093

Series: train\_data

ARIMA(1,0,0)(2,1,1)[4]

Coefficients:

	ar1	sar1	sar2	sma1
	0.9884	-0.0143	-0.3977	-0.7750
s.e.	0.0248	0.2300	0.2086	0.3428

$\sigma^2 = 7717$ : log likelihood = -237.29

AIC=484.58 AICc=486.35 BIC=493.03

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.3076179	79.46036	58.38744	0.001813533	1.151999	0.3388217

ACF1

Training set 0.06714897

Forecasts for Time Series ID: 1093

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5330.613	5215.966	5320.498	5154.868

1992 5338.371 5284.163 5378.066 5200.171

Summary for ARIMA model of Time Series ID: 1094

Series: train\_data

ARIMA(1,1,0)(0,1,1)[4]

Coefficients:

	ar1	sma1
	-0.3694	-0.7461
s.e.	0.1555	0.1687

$\sigma^2 = 2907$ : log likelihood = -211.49

AIC=428.98 AICc=429.67 BIC=433.97

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-12.17763	49.44308	35.23021	-0.2355123	0.6532785	0.1811205

ACF1

Training set 0.02152234

Forecasts for Time Series ID: 1094

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6444.222	6419.018	6394.629	6410.063
1992	6622.824	6602.593	6576.367	6592.479

Summary for ARIMA model of Time Series ID: 1095

Series: train\_data

ARIMA(2,1,0)(0,1,1)[4]

Coefficients:

	ar1	ar2	sma1
	-0.3257	0.5815	-0.6893
s.e.	0.1395	0.1716	0.2256

sigma^2 = 1382: log likelihood = -196.05  
AIC=400.1 AICc=401.28 BIC=406.75

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	2.978576	33.62524	25.63391	0.03162078	0.7043374	0.129966

ACF1  
Training set -0.07974485

Forecasts for Time Series ID: 1095

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4704.789	5169.176	4872.016	5378.465
1992	4991.281	5455.098	5148.708	5657.832

Summary for ARIMA model of Time Series ID: 1096

Series: train\_data

ARIMA(1,0,0)(0,1,1)[4] with drift

Coefficients:

	ar1	sma1	drift
	0.4034	-0.6198	60.2491
s.e.	0.1593	0.1431	5.8045

sigma^2 = 40616: log likelihood = -268.48  
AIC=544.96 AICc=546.1 BIC=551.71

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-9.14858	184.8093	133.3678	-1.146181	4.180651	0.4804271

ACF1

Training set -0.03136299

Forecasts for Time Series ID: 1096

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4309.480	4356.940	5907.685	5288.789
1992	4470.134	4565.526	6135.607	5524.511

Summary for ARIMA model of Time Series ID: 1097

Series: train\_data

ARIMA(1,0,0)(0,1,0)[4] with drift

Coefficients:

	ar1	drift
	0.8673	66.7194
s.e.	0.0747	6.2645

$\sigma^2 = 590.2$ : log likelihood = -184.01

AIC=374.03 AICc=374.69 BIC=379.09

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.03607343	22.57766	16.17088	-0.008022633	0.3854787	0.06317492

ACF1

Training set -0.04832301

Forecasts for Time Series ID: 1097

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5495.750	5796.655	5893.774	5899.987
1992	5792.039	6089.042	6182.777	6186.055

Summary for ARIMA model of Time Series ID: 1098

Series: train\_data

ARIMA(1,0,0)(0,1,0)[4] with drift

Coefficients:

	ar1	drift
	0.5959	68.7513
s.e.	0.1312	10.3321

$\sigma^2 = 12522$ : log likelihood = -244.65

AIC=495.31 AICc=495.98 BIC=500.38

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	1.383492	103.9946	80.68637	-0.044867	1.70771	0.2989381	0.01170303

Forecasts for Time Series ID: 1098

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6135.121	6221.546	6141.947	6922.794
1992	6428.711	6507.626	6423.551	7201.732

Summary for ARIMA model of Time Series ID: 1099

Series: train\_data

ARIMA(1,1,0)(1,1,0)[4]

Coefficients:

	ar1	sar1
	-0.4331	-0.3815
s.e.	0.1443	0.1727

sigma^2 = 2007: log likelihood = -203  
AIC=411.99 AICc=412.68 BIC=416.99

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	8.376976	41.08341	29.93077	0.1913548	0.862694	0.1489716

ACF1  
Training set -0.06714039

Forecasts for Time Series ID: 1099

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4474.509	4785.268	4939.125	5166.557
1992	4793.598	5115.951	5286.908	5504.979

Summary for ARIMA model of Time Series ID: 1100

Series: train\_data

ARIMA(0,0,0)(1,1,1)[4] with drift

Coefficients:

	sar1	sma1	drift
	-0.9125	0.5815	21.2252
s.e.	0.1001	0.2224	11.3208

sigma^2 = 126710: log likelihood = -291.57  
AIC=591.13 AICc=592.27 BIC=597.89



Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-14.12461	326.4223	214.5401	-0.4320085	3.537335	0.7214464
ACF1						

Training set 0.07352387

Forecasts for Time Series ID: 1100

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4445.256	4960.224	6504.951	8008.646
1992	4603.743	5138.358	6691.090	8250.724

**8.36** Code computing the average Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (sMAPE) for the ARIMA models, and comparing its performance with the Theta and Damped Exponential Smoothing models, which serve as benchmarks (benchmark models fitted in Appendix 8.35)

```
# Calculate average MAPE and sMAPE for each method
avg_mape_arima <- mean(mape_arima, na.rm = TRUE)
avg_smape_arima <- mean(smape_arima, na.rm = TRUE)
avg_mape_theta <- mean(mape_theta, na.rm = TRUE)
avg_smape_theta <- mean(smape_theta, na.rm = TRUE)
avg_mape_damped <- mean(mape_damped, na.rm = TRUE)
avg_smape_damped <- mean(smape_damped, na.rm = TRUE)

# Store evaluation metrics for each model in a data frame
arima_batch_evaluation_metrics <- data.frame(
```

```

Model = c("ARIMA", "Theta", "Damped Exponential Smoothing"),
MAPE = c(avg_mape_arma, avg_mape_theta, avg_mape_damped),
sMAPE = c(avg_smape_arma, avg_smape_theta, avg_smape_damped)
)

# Print the evaluation metrics for comparison
cat("Table 19: Error measures evaluating automatic ARIMA model's
    out-of-sample accuracy")
print(arma_batch_evaluation_metrics, row.names = FALSE)

# Select the model with the lowest values for MAPE
arma_batch_best_model_mape <- arma_batch_evaluation_metrics[which.min(
    arma_batch_evaluation_metrics$MAPE), ]

# Select the model with the lowest values for sMAPE
arma_batch_best_model_smape <- arma_batch_evaluation_metrics[which.min(
    arma_batch_evaluation_metrics$sMAPE), ]

# Print the best model
cat("Best model based on MAPE:", arma_batch_best_model_mape$Model, "\n")
cat("Best model based on sMAPE:", arma_batch_best_model_smape$Model, "\n")

```

**8.37** Code printing summaries of automatically fitted ETS models for each series (IDs 1001 to 1100) and printing respective forecasted values.

```

# Define the series IDs and criterion
ts_start <- 1001

```

```

ts_end <- 1100
criterion <- "aicc"
num_ts <- ts_end - ts_start + 1

# Initialize arrays to store MAPE and sMAPE for ETS and benchmarks
mape_ets <- numeric(num_ts)
smape_ets <- numeric(num_ts)
mape_theta <- numeric(num_ts)
smape_theta <- numeric(num_ts)
mape_damped <- numeric(num_ts)
smape_damped <- numeric(num_ts)

# Loop through each time series
for (s in ts_start:ts_end) {
  train_data <- M3[[s]]$x
  test_data <- M3[[s]]$xx
  h <- length(test_data)

  # Fit ETS model
  ets_fit <- ets(train_data)

  # Print summary of the fitted ETS model
  cat("Summary for ETS model of Time Series ID:", s, "\n")
  print(summary(ets_fit))
  cat("\n") # Add a newline after each summary

  ets_fcst <- forecast(ets_fit, h = h)$mean

  # Print forecasts
  cat("Forecasts for Time Series ID:", s, "\n")
  print(ets_fcst)
  cat("\n") # Add a newline after printing forecasts
}

```

```

# Calculate MAPE for ETS
mape_ets[s - ts_start + 1] <- 100 * mean(abs(test_data - ets_fcst) /
                                         test_data, na.rm = TRUE)

# Calculate sMAPE for ETS
smape_ets[s - ts_start + 1] <- 200 * mean(abs(test_data - ets_fcst) /
                                         (abs(test_data) + abs(ets_fcst)),
                                         na.rm = TRUE)

# Fit Theta model
theta_fit <- thetaf(train_data, h = h)
theta_fcst <- forecast(theta_fit)$mean

# Calculate MAPE for Theta
mape_theta[s - ts_start + 1] <- 100 * mean(abs(test_data - theta_fcst) /
                                           test_data, na.rm = TRUE)

# Calculate sMAPE for Theta
smape_theta[s - ts_start + 1] <- 200 * mean(abs(test_data - theta_fcst) /
                                           (abs(test_data) + abs(theta_fcst)),
                                           na.rm = TRUE)

# Fit Damped Exponential Smoothing model
tryCatch({
  damped_model <- ets(train_data, model = "ZZZ", damped = TRUE)
  damped_fcst <- forecast(damped_model, h = h)$mean
  # Calculate MAPE for Damped Exponential Smoothing
  mape_damped[s - ts_start + 1] <- 100 * mean(abs(test_data - damped_fcst) /
                                              test_data, na.rm = TRUE)
  # Calculate sMAPE for Damped Exponential Smoothing
  smape_damped[s - ts_start + 1] <- 200 * mean(abs(test_data - damped_fcst) /
                                              (abs(test_data) + abs(damped_fcst)),
                                              na.rm = TRUE)

```

```

na.rm = TRUE)

}, error = function(e) {
  mape_damped[s - ts_start + 1] <- NA # Assign NA in case of error
  smape_damped[s - ts_start + 1] <- NA # Assign NA in case of error
})
}

```

Summary for ETS model of Time Series ID: 1001

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9912

beta = 1e-04

Initial states:

l = 3239.3284

b = 82.6348

sigma: 0.0272

	AIC	AICc	BIC
	600.3259	601.9049	609.2469

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	4.126213	131.4635	101.1422	-0.05228997	2.061665	0.2424528
	ACF1					

Training set 0.1487912

Forecasts for Time Series ID: 1001

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7136.809	7219.462	7302.115	7384.768
1992	7467.421	7550.074	7632.726	7715.379

Summary for ETS model of Time Series ID: 1002

ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.5518

beta = 0.0918

Initial states:

l = 4266.2976

b = 0.4424

sigma: 116.2911

AIC	AICc	BIC
590.8472	592.4262	599.7682

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	21.16856	110.8792	83.91645	0.4023111	1.707774	0.3220125	-0.1078922

Forecasts for Time Series ID: 1002

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6751.164	6837.080	6922.997	7008.913
1992	7094.829	7180.746	7266.662	7352.579

Summary for ETS model of Time Series ID: 1003

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.7005

beta = 1e-04

Initial states:

l = 3953.6374

b = 54.0465

sigma: 0.0364

	AIC	AICc	BIC
	627.7882	629.3671	636.7091

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	10.29196	171.5243	143.6277	-0.008435124	2.948394	0.4693332

ACF1

Training set 0.08894812

Forecasts for Time Series ID: 1003

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6701.414	6755.506	6809.598	6863.690
1992	6917.782	6971.874	7025.965	7080.057

Summary for ETS model of Time Series ID: 1004

ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.282

beta = 1e-04

Initial states:

l = 3809.1182

b = 47.8075

sigma: 154.0684

AIC	AICc	BIC
615.6016	617.1806	624.5226

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-1.237137	146.8985	109.4963	-0.08473302	2.326103	0.4880873

ACF1

Training set -0.08249962



Forecasts for Time Series ID: 1004

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5945.904	5993.706	6041.508	6089.310
1992	6137.112	6184.914	6232.716	6280.519

Summary for ETS model of Time Series ID: 1005

ETS(M,Ad,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

beta = 0.9999

phi = 0.8002

Initial states:

l = 4141.8157

b = 34.3718

sigma: 0.0113

AIC	AICc	BIC
525.6753	527.9455	536.3804

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	5.850458	51.73885	43.91775	0.1324076	0.9043621	0.190667	0.3555957

Forecasts for Time Series ID: 1005

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5734.390	5701.091	5674.445	5653.123
1992	5636.060	5622.407	5611.482	5602.739

Summary for ETS model of Time Series ID: 1006  
ETS(M,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9999
```

Initial states:

```
l = 4541.1811
```

```
sigma: 0.0229
```

	AIC	AICc	BIC
	586.6916	587.2916	592.0442

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	32.71559	112.8353	95.34724	0.6011925	1.876999	0.4513212

ACF1

Training set -0.09516138

Forecasts for Time Series ID: 1006

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5980.494	5980.494	5980.494	5980.494

1992 5980.494 5980.494 5980.494 5980.494

Summary for ETS model of Time Series ID: 1007

ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

beta = 0.2884

Initial states:

l = 5288.6484

b = -20.8917

sigma: 115.8453

	AIC	AICc	BIC
	590.5092	592.0881	599.4301

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	13.86633	110.4541	96.23964	0.2731804	1.727167	0.2143601

ACF1

Training set -0.01500038

Forecasts for Time Series ID: 1007

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8604.572	8759.658	8914.744	9069.830

1992 9224.916 9380.002 9535.088 9690.174

Summary for ETS model of Time Series ID: 1008

ETS(M,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9854

Initial states:

l = 3838.0125

sigma: 0.0447

AIC	AICc	BIC
643.5541	644.1541	648.9066

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	56.00955	220.2785	173.744	1.037716	3.443078	0.3508209	0.2479603

Forecasts for Time Series ID: 1008

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6266.451	6266.451	6266.451	6266.451
1992	6266.451	6266.451	6266.451	6266.451

Summary for ETS model of Time Series ID: 1009

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9999
```

```
beta  = 0.0779
```

Initial states:

```
l = 4269.905
```

```
b = 15.8099
```

```
sigma: 0.027
```

	AIC	AICc	BIC
	602.3907	603.9696	611.3116

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	23.81506	131.5912	109.5343	0.4084176	2.162187	0.3612907

ACF1

Training set	0.004897337
--------------	-------------

Forecasts for Time Series ID: 1009

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6946.894	7044.306	7141.718	7239.129
1992	7336.541	7433.953	7531.365	7628.777

Summary for ETS model of Time Series ID: 1010

ETS(A,Ad,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

beta = 0.5172

phi = 0.8

Initial states:

l = 4026.5899

b = 18.2219

sigma: 167.7542

	AIC	AICc	BIC
	623.9767	626.2470	634.6818

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	17.96498	157.9354	117.0232	0.3776026	2.473335	0.2526477

ACF1

Training set -0.01609635

Forecasts for Time Series ID: 1010

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6853.465	6787.826	6735.314	6693.305
1992	6659.698	6632.812	6611.303	6594.096

Summary for ETS model of Time Series ID: 1011

ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 1e-04
```

```
beta  = 1e-04
```

Initial states:

```
l = 5099.3612
```

```
b = 40.3096
```

```
sigma: 89.2441
```

	AIC	AICc	BIC
	193.4825	199.4825	197.3455

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.1964456	77.28766	61.83139	-0.01664789	1.139897	0.3796248

ACF1

Training set 0.00251277

Forecasts for Time Series ID: 1011

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5784.630	5824.940	5865.250	5905.560
1992	5945.870	5986.179	6026.489	6066.799

Summary for ETS model of Time Series ID: 1012

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.1964

beta = 0.1964

Initial states:

l = 4750.0529

b = -122.5867

sigma: 0.0602

AIC	AICc	BIC
678.5313	680.1102	687.4522

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-8.136966	323.5669	229.5736	-0.1765128	4.326737	0.5925819

ACF1

Training set -0.1359656

Forecasts for Time Series ID: 1012

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6739.687	6546.768	6353.850	6160.932
1992	5968.013	5775.095	5582.176	5389.258

Summary for ETS model of Time Series ID: 1013



ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.4515

beta = 0.1158

Initial states:

l = 4805.4074

b = -24.029

sigma: 141.5039

	AIC	AICc	BIC
	608.1155	609.6944	617.0364

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	24.26242	134.9186	104.2716	0.4544796	1.972449	0.3420844	0.02512423

Forecasts for Time Series ID: 1013

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7445.735	7545.362	7644.990	7744.618
1992	7844.245	7943.873	8043.500	8143.128

Summary for ETS model of Time Series ID: 1014

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.63
```

```
beta  = 0.2017
```

Initial states:

```
l = 4679.1573
```

```
b = -34.9959
```

```
sigma: 0.0222
```

	AIC	AICc	BIC
	588.7626	590.3416	597.6836

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	31.58617	109.7391	84.79316	0.5270291	1.633305	0.3097608

ACF1

Training set -0.007781782

Forecasts for Time Series ID: 1014

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7577.651	7823.025	8068.399	8313.774
1992	8559.148	8804.522	9049.897	9295.271

Summary for ETS model of Time Series ID: 1015

ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.7013
```

```
beta  = 0.0966
```

Initial states:

```
l = 4429.7437
```

```
b = 0.4176
```

```
sigma: 136.7076
```

AIC	AICc	BIC
-----	------	-----

605.081	606.660	614.002
---------	---------	---------

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	24.26548	130.3456	104.0812	0.4403061	2.059983	0.3419645

ACF1

Training set -0.02331057

Forecasts for Time Series ID: 1015

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7179.936	7283.545	7387.153	7490.762
1992	7594.371	7697.980	7801.588	7905.197

Summary for ETS model of Time Series ID: 1016

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9999
```

```
beta  = 0.2782
```

Initial states:

```
l = 4632.1274
```

```
b = 36.9938
```

```
sigma: 0.034
```

	AIC	AICc	BIC
	634.6627	636.2417	643.5837

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	4.966961	201.4591	147.6251	0.1613788	2.509526	0.2541318	0.02938582

Forecasts for Time Series ID: 1016

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9195.325	9293.125	9390.925	9488.725
1992	9586.526	9684.326	9782.126	9879.926

Summary for ETS model of Time Series ID: 1017

ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.2906

beta = 0.2258

Initial states:

l = 4731.4604

b = -135.3046

sigma: 117.3949

AIC	AICc	BIC
591.6785	593.2574	600.5994

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	16.24765	111.9316	87.2451	0.3885996	1.728419	0.3375215	0.1798649

Forecasts for Time Series ID: 1017

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6691.562	6717.701	6743.840	6769.979
1992	6796.118	6822.257	6848.396	6874.535

Summary for ETS model of Time Series ID: 1018

ETS(M,N,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9941

Initial states:

l = 4183.5761

sigma: 0.0362

	AIC	AICc	BIC
	623.0375	623.6375	628.3900

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	22.06832	170.9744	133.0633	0.4137491	2.728301	0.4787526

ACF1

Training set -0.003650548

Forecasts for Time Series ID: 1018

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5148.866	5148.866	5148.866	5148.866
1992	5148.866	5148.866	5148.866	5148.866

Summary for ETS model of Time Series ID: 1019

ETS(A,N,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.8577

Initial states:

l = 4695.0495

sigma: 187.6144

	AIC	AICc	BIC
	631.0837	631.6837	636.4362

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	39.31715	183.3008	132.4284	0.6506816	2.589166	0.4872274

ACF1

Training set -0.05949501

Forecasts for Time Series ID: 1019

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6178.83	6178.83	6178.83	6178.83
1992	6178.83	6178.83	6178.83	6178.83

Summary for ETS model of Time Series ID: 1020

ETS(A,Ad,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9999

beta = 0.9999

phi = 0.8

Initial states:

l = 4435.9748

b = 8.2928

sigma: 70.7856

AIC	AICc	BIC
548.0464	550.3166	558.7515

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	7.022565	66.64241	56.89313	0.1460096	1.14146	0.2325134	0.09503864

Forecasts for Time Series ID: 1020

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6257.191	6208.545	6169.629	6138.495
1992	6113.588	6093.663	6077.722	6064.970

Summary for ETS model of Time Series ID: 1021

ETS(A,N,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9999

Initial states:

l = 4413.4281



sigma: 172.9667

AIC	AICc	BIC
623.9302	624.5302	629.2828

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	55.78016	168.9899	142.6897	0.9452835	2.798246	0.3882054	0.2103819

Forecasts for Time Series ID: 1021

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6867.509	6867.509	6867.509	6867.509
1992	6867.509	6867.509	6867.509	6867.509

Summary for ETS model of Time Series ID: 1022

ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

beta = 1e-04

Initial states:

l = 3178.462

b = 70.0446

sigma: 128.939

AIC	AICc	BIC
599.9325	601.5115	608.8535

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-3.486333	122.9385	99.73822	-0.1419222	2.363118	0.3203411

ACF1

Training set 0.1301864

Forecasts for Time Series ID: 1022

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6177.050	6247.079	6317.108	6387.138
1992	6457.167	6527.196	6597.225	6667.255

Summary for ETS model of Time Series ID: 1023

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.265

beta = 0.028

Initial states:

l = 2611.234

b = 115.8404

sigma: 0.0212

	AIC	AICc	BIC
	584.1612	585.7402	593.0822

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	26.51517	105.2873	85.33039	0.3533057	1.653142	0.1630076	0.1146259

Forecasts for Time Series ID: 1023

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8451.449	8599.940	8748.432	8896.924
1992	9045.416	9193.908	9342.400	9490.892

Summary for ETS model of Time Series ID: 1024

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

beta = 0.2995

Initial states:

l = 1437.9697

b = 68.9562

sigma: 0.0331

	AIC	AICc	BIC
	569.6966	571.2756	578.6176

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-8.730959	103.9484	76.56922	-0.1946682	2.579851	0.233162

ACF1

Training set 0.03697413

Forecasts for Time Series ID: 1024

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4144.121	4098.037	4051.953	4005.869
1992	3959.785	3913.701	3867.616	3821.532

Summary for ETS model of Time Series ID: 1025

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.6768

beta = 0.0749

Initial states:

l = 2779.3415

b = 41.9733

sigma: 0.053

	AIC	AICc	BIC
	654.2017	655.7806	663.1226

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	36.04055	236.9976	185.5997	0.6656223	3.966016	0.3432582

ACF1

Training set 0.007722159

Forecasts for Time Series ID: 1025

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8261.792	8422.522	8583.252	8743.982
1992	8904.712	9065.442	9226.172	9386.902

Summary for ETS model of Time Series ID: 1026

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9973  
beta  = 1e-04
```

Initial states:

```
l = 2606.4597  
b = 121.6033
```

```
sigma: 0.0461
```

	AIC	AICc	BIC
	652.1293	653.7082	661.0502

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	6.816727	244.8715	180.7851	-0.06517335	3.36706	0.2946842

ACF1

Training set 0.002726185

Forecasts for Time Series ID: 1026

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8377.945	8499.578	8621.211	8742.845
1992	8864.478	8986.111	9107.745	9229.378

Summary for ETS model of Time Series ID: 1027

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9999  
beta  = 0.1691
```

Initial states:

```
l = 3037.9063  
b = 104.0715
```

```
sigma: 0.0128
```

	AIC	AICc	BIC
	549.233	550.812	558.154

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	5.276471	74.91439	55.89489	0.1246731	0.9220461	0.09072557

ACF1

Training set 0.1218228

Forecasts for Time Series ID: 1027

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9690.925	9834.245	9977.565	10120.885
1992	10264.205	10407.525	10550.845	10694.165

Summary for ETS model of Time Series ID: 1028

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.8459

beta = 1e-04

Initial states:

l = 3927.1947

b = 34.4953

sigma: 0.0087

	AIC	AICc	BIC
	497.8685	499.4475	506.7895

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-0.7005015	39.05971	30.41571	-0.02424047	0.6524491	0.2124484
ACF1						
Training set	0.02509888					

Forecasts for Time Series ID: 1028

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5453.210	5487.702	5522.194	5556.686
1992	5591.179	5625.671	5660.163	5694.656

Summary for ETS model of Time Series ID: 1029

ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.3941  
beta  = 3e-04
```

Initial states:

```
l = 5408.3955  
b = 58.2576
```

```
sigma: 120.7161
```

AIC	AICc	BIC
594.1335	595.7125	603.0545



Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-0.1399029	115.0983	92.35358	-0.05504651	1.42598	0.3512712

ACF1

Training set -0.007251207

Forecasts for Time Series ID: 1029

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8024.735	8082.991	8141.246	8199.502
1992	8257.757	8316.013	8374.268	8432.523

Summary for ETS model of Time Series ID: 1030

ETS(M,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

Initial states:

l = 3200.3074

sigma: 0.0323

	AIC	AICc	BIC
	593.4200	594.0200	598.7726

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	21.20451	122.7163	99.17852	0.5320504	2.576993	0.3421129	0.2360295

Forecasts for Time Series ID: 1030

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4133.212	4133.212	4133.212	4133.212
1992	4133.212	4133.212	4133.212	4133.212

Summary for ETS model of Time Series ID: 1031

ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.7482

beta = 1e-04

Initial states:

l = 4536.546

b = 81.9705

sigma: 242.7631

	AIC	AICc	BIC
	655.6143	657.1932	664.5352

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-0.9796895	231.4655	189.9726	-0.2981587	3.444144	0.4170411

ACF1

Training set 0.005581536

Forecasts for Time Series ID: 1031

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8190.000	8271.967	8353.933	8435.899
1992	8517.865	8599.831	8681.798	8763.764

Summary for ETS model of Time Series ID: 1032

ETS(M,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

Initial states:

l = 4796.5196

sigma: 0.0445

AIC	AICc	BIC
663.1561	663.7561	668.5086

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	69.7008	275.4024	216.9731	1.032664	3.42148	0.3488524	0.2285864

Forecasts for Time Series ID: 1032

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7863.047	7863.047	7863.047	7863.047
1992	7863.047	7863.047	7863.047	7863.047

Summary for ETS model of Time Series ID: 1033  
ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.998

beta = 1e-04

Initial states:

l = 6622.1422

b = 58.499

sigma: 85.8906

	AIC	AICc	BIC
	564.1813	565.7602	573.1022

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.882954	81.89349	68.20942	-0.005010301	0.882314	0.2450931

ACF1

Training set 0.1209959

Forecasts for Time Series ID: 1033

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9293.083	9351.586	9410.089	9468.592
1992	9527.095	9585.598	9644.101	9702.603

Summary for ETS model of Time Series ID: 1034  
ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.7705

beta = 1e-04

Initial states:

l = 2462.6707

b = 63.451

sigma: 41.0786

	AIC	AICc	BIC
	499.2736	500.8526	508.1946

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-0.1004707	39.16693	32.86079	0.02544259	0.8770825	0.1295326

ACF1

Training set -0.03555657

Forecasts for Time Series ID: 1034

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5314.868	5378.319	5441.769	5505.220
1992	5568.670	5632.121	5695.571	5759.022

Summary for ETS model of Time Series ID: 1035  
ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9338

beta = 0.5512

Initial states:

l = 2255.5435

b = 54.6724

sigma: 0.0093

	AIC	AICc	BIC
	481.5433	483.1223	490.4643

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-1.407889	34.09857	25.07492	-0.01402281	0.6687911	0.09460003

ACF1

Training set -0.02354118

Forecasts for Time Series ID: 1035

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5086.538	5107.067	5127.597	5148.126
1992	5168.655	5189.184	5209.713	5230.243

Summary for ETS model of Time Series ID: 1036  
ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9999
beta  = 5e-04
```

Initial states:

```
l = 3018.6132
b = 45.9072
```

```
sigma: 0.0238
```

	AIC	AICc	BIC
	572.0967	573.6756	581.0176

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-0.9207865	92.0135	70.91509	-0.06442032	1.747482	0.3418213

ACF1

Training set 0.04487423

Forecasts for Time Series ID: 1036

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5042.887	5088.775	5134.663	5180.551
1992	5226.440	5272.328	5318.216	5364.104

Summary for ETS model of Time Series ID: 1037  
ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

beta = 3e-04

Initial states:

l = 2899.2956

b = 57.5828

sigma: 0.0326

	AIC	AICc	BIC
	603.5659	605.1448	612.4868

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-4.160498	138.1855	97.99897	-0.1292752	2.216211	0.3537869
ACF1						
Training set	0.04805104					

Forecasts for Time Series ID: 1037



	Qtr1	Qtr2	Qtr3	Qtr4
1991	5307.512	5365.048	5422.584	5480.120
1992	5537.656	5595.192	5652.728	5710.264

Summary for ETS model of Time Series ID: 1038  
ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9999
beta  = 0.1018
```

Initial states:

```
l = 1550.7188
b = 72.0316
```

```
sigma: 0.0146
```

	AIC	AICc	BIC
	502.6509	504.2299	511.5719

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	3.442395	41.71861	31.40408	0.04338443	1.049344	0.1023451	0.25206

Forecasts for Time Series ID: 1038

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4933.154	5020.601	5108.049	5195.497

1992 5282.945 5370.393 5457.841 5545.288

Summary for ETS model of Time Series ID: 1039

ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9008

beta = 0.2789

Initial states:

l = 2287.7009

b = 81.554

sigma: 115.7322

	AIC	AICc	BIC
	590.4233	592.0022	599.3442

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-1.877698	110.3464	89.27653	0.01558501	2.141512	0.1898652

ACF1

Training set -0.02578994

Forecasts for Time Series ID: 1039

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7238.154	7296.663	7355.172	7413.681

1992 7472.190 7530.699 7589.208 7647.717

Summary for ETS model of Time Series ID: 1040

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.7193

beta = 1e-04

Initial states:

l = 1651.5676

b = 79.6336

sigma: 0.0401

	AIC	AICc	BIC
	602.0929	603.6719	611.0139

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	13.12781	137.5924	104.5709	0.08578214	2.955385	0.2682422

ACF1

Training set 0.01233195

Forecasts for Time Series ID: 1040

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5651.116	5730.808	5810.499	5890.190

1992 5969.882 6049.573 6129.264 6208.956

Summary for ETS model of Time Series ID: 1041

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

beta = 0.1691

Initial states:

l = 3037.9063

b = 104.0715

sigma: 0.0128

	AIC	AICc	BIC
	549.233	550.812	558.154

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	5.276471	74.91439	55.89489	0.1246731	0.9220461	0.09072557

ACF1

Training set 0.1218228

Forecasts for Time Series ID: 1041

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9690.925	9834.245	9977.565	10120.885

1992 10264.205 10407.525 10550.845 10694.165

Summary for ETS model of Time Series ID: 1042

ETS(A,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.8893
```

Initial states:

```
l = 3569.378
```

```
sigma: 462.812
```

	AIC	AICc	BIC
	710.5417	711.1417	715.8943

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	53.91049	452.1712	259.4539	0.5951371	5.520216	0.3952078

ACF1

Training set -0.02634482

Forecasts for Time Series ID: 1042

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5678.816	5678.816	5678.816	5678.816
1992	5678.816	5678.816	5678.816	5678.816

Summary for ETS model of Time Series ID: 1043

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

beta = 0.1627

Initial states:

l = 2841.793

b = 109.1369

sigma: 0.0119

AIC	AICc	BIC
539.3723	540.9513	548.2933

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	5.754248	68.12513	53.857	0.1200653	0.9152801	0.08940888	0.1230461

Forecasts for Time Series ID: 1043

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9415.243	9565.581	9715.919	9866.257
1992	10016.595	10166.933	10317.272	10467.610

Summary for ETS model of Time Series ID: 1044

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9999
```

```
beta  = 0.1691
```

Initial states:

```
l = 3037.9063
```

```
b = 104.0715
```

```
sigma: 0.0128
```

	AIC	AICc	BIC
	549.233	550.812	558.154

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	5.276471	74.91439	55.89489	0.1246731	0.9220461	0.09072557

ACF1

Training set	0.1218228
--------------	-----------

Forecasts for Time Series ID: 1044

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9690.925	9834.245	9977.565	10120.885
1992	10264.205	10407.525	10550.845	10694.165

Summary for ETS model of Time Series ID: 1045

ETS(A,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9406
```

Initial states:

```
l = 5304.1437
```

```
sigma: 520.2362
```

	AIC	AICc	BIC
	720.8344	721.4344	726.1869

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	48.4998	508.2752	275.9132	0.3287836	4.778733	0.3926472

ACF1

Training set -0.003785845

Forecasts for Time Series ID: 1045

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7311.431	7311.431	7311.431	7311.431
1992	7311.431	7311.431	7311.431	7311.431

Summary for ETS model of Time Series ID: 1046

ETS(M,A,N)

Call:



```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9879
```

```
beta  = 1e-04
```

Initial states:

```
l = 6290.3001
```

```
b = 57.0976
```

```
sigma: 0.0105
```

	AIC	AICc	BIC
	556.9769	558.5558	565.8978

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	1.526496	75.36663	63.30666	0.009103625	0.8394594	0.2465213

ACF1

Training set 0.1976588

Forecasts for Time Series ID: 1046

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8926.027	8983.131	9040.235	9097.340
1992	9154.444	9211.548	9268.653	9325.757

Summary for ETS model of Time Series ID: 1047

ETS(A,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.998
```

```
beta  = 1e-04
```

Initial states:

```
l = 6622.1422
```

```
b = 58.499
```

```
sigma: 85.8906
```

	AIC	AICc	BIC
	564.1813	565.7602	573.1022

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.882954	81.89349	68.20942	-0.005010301	0.882314	0.2450931

ACF1

Training set 0.1209959

Forecasts for Time Series ID: 1047

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9293.083	9351.586	9410.089	9468.592
1992	9527.095	9585.598	9644.101	9702.603

Summary for ETS model of Time Series ID: 1048

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9999
```

```
beta  = 0.9999
```

Initial states:

```
l = 2250.3933
```

```
b = 69.8385
```

```
sigma: 0.0053
```

	AIC	AICc	BIC
	449.2109	450.7898	458.1318

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.09449977	22.93464	18.5772	0.02890167	0.4111384	0.03971716

ACF1

Training set 0.1153727

Forecasts for Time Series ID: 1048

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7322.494	7396.490	7470.486	7544.482
1992	7618.478	7692.474	7766.471	7840.467

Summary for ETS model of Time Series ID: 1049

ETS(M,A,A)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9995

beta = 1e-04

gamma = 1e-04

Initial states:

l = 1406.2569

b = 46.302

s = 523.9656 -13.3425 -338.0059 -172.6173

sigma: 0.07

	AIC	AICc	BIC
	620.4997	625.7939	636.5574

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-0.4644707	149.053	116.3146	-0.2795175	5.084622	0.3688371	0.190879

Forecasts for Time Series ID: 1049

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3296.706	3177.612	3548.592	4132.129
1992	3481.905	3362.812	3733.792	4317.328

Summary for ETS model of Time Series ID: 1050

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.6041
```

```
beta  = 2e-04
```

Initial states:

```
l = 1791.9554
```

```
b = 56.9899
```

```
sigma: 0.054
```

	AIC	AICc	BIC
	619.7744	621.3534	628.6954

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-5.665167	171.127	119.5778	-0.3637929	3.842223	0.3806999	0.1242307

Forecasts for Time Series ID: 1050

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4206.359	4263.301	4320.242	4377.183
1992	4434.125	4491.066	4548.007	4604.949

Summary for ETS model of Time Series ID: 1051

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9983

beta = 0.2757

Initial states:

l = 1251.9933

b = 83.2152

sigma: 0.0379

AIC	AICc	BIC
571.5327	573.1116	580.4536

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-9.896517	105.7415	75.81354	-0.3143305	2.898451	0.2407505

ACF1

Training set 0.01332194

Forecasts for Time Series ID: 1051

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3751.008	3714.165	3677.322	3640.479
1992	3603.636	3566.793	3529.950	3493.107

Summary for ETS model of Time Series ID: 1052

ETS(M,A,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9999

beta = 0.2995

Initial states:

l = 1437.9697

b = 68.9562

sigma: 0.0331

	AIC	AICc	BIC
	569.6966	571.2756	578.6176

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-8.730959	103.9484	76.56922	-0.1946682	2.579851	0.233162

ACF1

Training set 0.03697413

Forecasts for Time Series ID: 1052

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4144.121	4098.037	4051.953	4005.869
1992	3959.785	3913.701	3867.616	3821.532

Summary for ETS model of Time Series ID: 1053

ETS(M,Ad,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.8086

beta = 0.8086

phi = 0.8025

Initial states:

l = 1493.4165

b = 159.9101

sigma: 0.0454

	AIC	AICc	BIC
	597.1514	599.4217	607.8565

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	11.54429	121.9716	92.84828	0.4986724	3.330173	0.2234481

ACF1

Training set -0.02377087

Forecasts for Time Series ID: 1053

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4326.897	4306.399	4289.949	4276.748
1992	4266.153	4257.651	4250.827	4245.351

Summary for ETS model of Time Series ID: 1054

ETS(M,A,N)

Call:

ets(y = train\_data)



Smoothing parameters:

alpha = 0.9982

beta = 0.1757

Initial states:

l = 1569.5861

b = 165.697

sigma: 0.0628

AIC	AICc	BIC
658.3826	659.9615	667.3035

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-18.20897	305.8269	219.4368	-0.3764088	4.795713	0.2740563

ACF1

Training set 0.2422269

Forecasts for Time Series ID: 1054

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7670.963	7695.865	7720.768	7745.670
1992	7770.573	7795.476	7820.378	7845.281

Summary for ETS model of Time Series ID: 1055

ETS(M,A,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9375

beta = 1e-04

Initial states:

l = 2236.1873

b = 112.0693

sigma: 0.055

	AIC	AICc	BIC
	657.0869	658.6659	666.0079

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-15.82483	272.7893	209.9632	-0.4131218	4.300731	0.3493564

ACF1

Training set 0.07902627

Forecasts for Time Series ID: 1055

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6626.417	6738.417	6850.416	6962.416
1992	7074.416	7186.415	7298.415	7410.415

Summary for ETS model of Time Series ID: 1056

ETS(M,Ad,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9999

beta = 0.6734

phi = 0.8

Initial states:

l = 1849.7988

b = 31.6942

sigma: 0.0743

	AIC	AICc	BIC
	662.3445	664.6148	673.0496

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	21.23359	411.8406	268.3326	0.8617495	5.675488	0.2535925	0.02967799

Forecasts for Time Series ID: 1056

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5881.488	5790.693	5718.056	5659.947
1992	5613.460	5576.270	5546.518	5522.716

Summary for ETS model of Time Series ID: 1057

ETS(M,A,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.8378

beta = 0.6395

Initial states:

l = 2391.8995

b = 201.013

sigma: 0.0382

AIC	AICc	BIC
634.3147	635.8937	643.2357

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-10.69232	200.4079	155.0354	-0.1127814	2.928059	0.2099044

ACF1

Training set 0.05377627

Forecasts for Time Series ID: 1057

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7825.878	7726.020	7626.161	7526.303
1992	7426.444	7326.585	7226.727	7126.868

Summary for ETS model of Time Series ID: 1058

ETS(M,N,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.6119

Initial states:

l = 3739.3074

sigma: 0.0531

	AIC	AICc	BIC
	639.8638	640.4638	645.2164

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	11.72587	205.5779	156.8057	0.1032196	4.035893	0.5697883	0.05085248

Forecasts for Time Series ID: 1058

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4055.012	4055.012	4055.012	4055.012
1992	4055.012	4055.012	4055.012	4055.012

Summary for ETS model of Time Series ID: 1059

ETS(M,N,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9999

Initial states:

l = 2830.8656

sigma: 0.0365

	AIC	AICc	BIC
	594.5527	595.1527	599.9053

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	20.63714	124.4355	99.2383	0.5692944	2.871767	0.3344623	0.2044762

Forecasts for Time Series ID: 1059

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3738.809	3738.809	3738.809	3738.809
1992	3738.809	3738.809	3738.809	3738.809

Summary for ETS model of Time Series ID: 1060

ETS(M,N,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9999

Initial states:

l = 3200.3074

sigma: 0.0323

	AIC	AICc	BIC
	593.4200	594.0200	598.7726

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	21.20451	122.7163	99.17852	0.5320504	2.576993	0.3421129	0.2360295

Forecasts for Time Series ID: 1060

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4133.212	4133.212	4133.212	4133.212
1992	4133.212	4133.212	4133.212	4133.212

Summary for ETS model of Time Series ID: 1061

ETS(A,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

Initial states:

l = 4100.6341

sigma: 200.7743

	AIC	AICc	BIC
	637.0494	637.6494	642.4020

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	2.531426	196.1582	160.1289	-0.05239835	3.871802	0.3362993

ACF1

Training set 0.4267028

Forecasts for Time Series ID: 1061

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4212.006	4212.006	4212.006	4212.006
1992	4212.006	4212.006	4212.006	4212.006

Summary for ETS model of Time Series ID: 1062

ETS(M,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

Initial states:

l = 3745.8634

sigma: 0.0635

	AIC	AICc	BIC
	685.4280	686.0280	690.7806

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	84.05707	354.1612	267.8752	1.378923	4.584946	0.3493417	0.2671659



Forecasts for Time Series ID: 1062

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7444.004	7444.004	7444.004	7444.004
1992	7444.004	7444.004	7444.004	7444.004

Summary for ETS model of Time Series ID: 1063

ETS(M,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9807

Initial states:

l = 4291.9845

sigma: 0.0603

AIC	AICc	BIC
682.7168	683.3168	688.0693

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	48.38261	335.9753	254.9718	0.7526733	4.393948	0.3799454	0.02556142

Forecasts for Time Series ID: 1063

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6379.717	6379.717	6379.717	6379.717

1992 6379.717 6379.717 6379.717 6379.717

Summary for ETS model of Time Series ID: 1064

ETS(M,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

Initial states:

l = 6125.4804

sigma: 0.0699

AIC	AICc	BIC
710.6544	711.2544	716.0070

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	20.33181	484.8095	373.0713	0.07654764	5.452458	0.3503839	0.3732546

Forecasts for Time Series ID: 1064

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7019.99	7019.99	7019.99	7019.99
1992	7019.99	7019.99	7019.99	7019.99

Summary for ETS model of Time Series ID: 1065

ETS(M,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9999
```

Initial states:

```
l = 5697.9276
```

```
sigma: 0.0413
```

	AIC	AICc	BIC
	668.4277	669.0277	673.7803

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	49.06372	281.4081	236.8665	0.6502471	3.366511	0.3223441	0.3835562

Forecasts for Time Series ID: 1065

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7856.515	7856.515	7856.515	7856.515
1992	7856.515	7856.515	7856.515	7856.515

Summary for ETS model of Time Series ID: 1066

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.8925

beta = 0.0727

Initial states:

l = 2161.8899

b = 75.2331

sigma: 0.0104

	AIC	AICc	BIC
	495.7267	497.3056	504.6476

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	6.984251	38.75817	29.54347	0.1353523	0.7602039	0.08483409

ACF1

Training set 0.1367202

Forecasts for Time Series ID: 1066

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6058.147	6155.715	6253.284	6350.853
1992	6448.421	6545.990	6643.558	6741.127

Summary for ETS model of Time Series ID: 1067

ETS(M,A,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.4238

beta = 0.1358

Initial states:

l = 2519.6694

b = 82.4839

sigma: 0.0217

AIC	AICc	BIC
574.052	575.631	582.973

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-8.671643	99.14112	72.27221	-0.122814	1.546111	0.2026702

ACF1

Training set -0.09818945

Forecasts for Time Series ID: 1067

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6390.262	6420.939	6451.616	6482.293
1992	6512.971	6543.648	6574.325	6605.002

Summary for ETS model of Time Series ID: 1068

ETS(M,A,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9999

beta = 0.0688

Initial states:

l = 2781.1327

b = 101.5022

sigma: 0.0226

AIC	AICc	BIC
588.0627	589.6417	596.9837

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	24.43454	120.6678	79.29798	0.3098768	1.525428	0.1421812	0.04807232

Forecasts for Time Series ID: 1068

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8984.473	9159.943	9335.413	9510.883
1992	9686.352	9861.822	10037.292	10212.761

Summary for ETS model of Time Series ID: 1069

ETS(M,A,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9217

beta = 1e-04

Initial states:

l = 2705.4725

b = 106.5455

sigma: 0.0188

	AIC	AICc	BIC
	571.7109	573.2898	580.6318

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	-4.281421	101.961	74.88988	-0.05711421	1.390997	0.1650284	0.150749

Forecasts for Time Series ID: 1069

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7326.779	7433.305	7539.832	7646.359
1992	7752.885	7859.412	7965.939	8072.465

Summary for ETS model of Time Series ID: 1070

ETS(M,A,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.8067

beta = 0.2752

Initial states:

l = 2378.8352

b = 87.9501

sigma: 0.0094

	AIC	AICc	BIC
	508.6376	510.2165	517.5585

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	5.309458	46.53471	38.56272	0.1513055	0.7743448	0.06321758

ACF1

Training set 0.0793359

Forecasts for Time Series ID: 1070

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9045.565	9197.797	9350.030	9502.263
1992	9654.495	9806.728	9958.960	10111.193

Summary for ETS model of Time Series ID: 1071

ETS(A,A,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9995

beta = 1e-04



Initial states:

l = 5265.9828

b = 18.2886

sigma: 57.0185

	AIC	AICc	BIC
	300.6226	303.6226	306.9131

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	0.3298402	52.44939	46.04505	4.993715e-05	0.839871	0.41212

ACF1

Training set 0.1573392

Forecasts for Time Series ID: 1071

	Qtr1	Qtr2	Qtr3	Qtr4
1992			5768.300	5786.590
1993	5804.879	5823.168	5841.458	5859.747
1994	5878.037	5896.326		

Summary for ETS model of Time Series ID: 1072

ETS(M,N,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.5254

Initial states:

l = 6089.626

sigma: 0.0233

	AIC	AICc	BIC
	348.1648	349.2557	351.9391

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	4.311375	142.1273	111.378	0.03359157	1.757642	0.70533	-0.1463669

Forecasts for Time Series ID: 1072

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6148.525	6148.525	6148.525	6148.525
1992	6148.525	6148.525	6148.525	6148.525

Summary for ETS model of Time Series ID: 1073

ETS(A,N,N)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9999

Initial states:

l = 6320.1367

sigma: 217.2531

AIC	AICc	BIC
368.4447	369.5356	372.2190

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	65.92571	208.73	167.2402	0.8785088	2.353786	0.425843	-0.09839429

Forecasts for Time Series ID: 1073

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8034.031	8034.031	8034.031	8034.031
1992	8034.031	8034.031	8034.031	8034.031

Summary for ETS model of Time Series ID: 1074

ETS(A,N,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9999

Initial states:

l = 6110.2862

sigma: 143.5578

AIC	AICc	BIC
346.8998	347.9907	350.6741

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	37.60861	137.9259	113.474	0.5500061	1.664781	0.3928909	0.08490943

Forecasts for Time Series ID: 1074

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7088.012	7088.012	7088.012	7088.012
1992	7088.012	7088.012	7088.012	7088.012

Summary for ETS model of Time Series ID: 1075

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.5197

beta = 0.4293

Initial states:

l = 6146.1166

b = 101.717

sigma: 0.0083

AIC	AICc	BIC
304.9908	307.9908	311.2813

Training set error measures:

ME	RMSE	MAE	MPE	MAPE	MASE
----	------	-----	-----	------	------

Training set -10.55288 58.04296 48.32071 -0.1270145 0.6485127 0.1313225

ACF1

Training set -0.05655147

Forecasts for Time Series ID: 1075

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8421.612	8405.533	8389.455	8373.376
1992	8357.297	8341.218	8325.140	8309.061

Summary for ETS model of Time Series ID: 1076

ETS(M,A,N)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.8459

beta = 1e-04

Initial states:

l = 3927.1947

b = 34.4953

sigma: 0.0087

AIC	AICc	BIC
497.8685	499.4475	506.7895

Training set error measures:

ME	RMSE	MAE	MPE	MAPE	MASE
----	------	-----	-----	------	------

Training set -0.7005015 39.05971 30.41571 -0.02424047 0.6524491 0.2124484

ACF1

Training set 0.02509888

Forecasts for Time Series ID: 1076

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5453.210	5487.702	5522.194	5556.686
1992	5591.179	5625.671	5660.163	5694.656

Summary for ETS model of Time Series ID: 1077

ETS(M,A,M)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.6214

beta = 5e-04

gamma = 1e-04

Initial states:

l = 2631.8311

b = 58.0655

s = 1.0871 0.9996 0.9853 0.928

sigma: 0.0129

AIC	AICc	BIC
-----	------	-----

517.6076	522.9018	533.6654
----------	----------	----------

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-4.311584	46.48302	34.86389	-0.1405482	0.900051	0.1555039

ACF1

Training set 0.1038392

Forecasts for Time Series ID: 1077

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4757.536	5108.655	5240.496	5762.220
1992	4972.722	5337.139	5472.284	6014.297

Summary for ETS model of Time Series ID: 1078

ETS(M,A,M)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.9589

beta = 0.0462

gamma = 8e-04

Initial states:

l = 4286.4055

b = 107.2432

s = 0.9551 0.9958 0.9852 1.0638

sigma: 0.0094

AIC	AICc	BIC
-----	------	-----

533.0512 538.3453 549.1089

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-8.050128	53.08004	41.25156	-0.1451886	0.658414	0.1168343

ACF1

Training set -0.01014735

Forecasts for Time Series ID: 1078

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8803.743	8243.457	8422.997	8165.682
1992	9192.006	8603.046	8786.454	8514.276

Summary for ETS model of Time Series ID: 1079

ETS(M,A,M)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.4568

beta = 0.1038

gamma = 1e-04

Initial states:

l = 3191.084

b = 34.5096

s = 1.1198 1.1536 1.029 0.6976

sigma: 0.0298



AIC	AICc	BIC
592.9109	598.2051	608.9686

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	15.14118	112.7096	80.70632	0.3100376	2.032878	0.3236084

ACF1

Training set -0.03054436

Forecasts for Time Series ID: 1079

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4020.025	6039.998	6894.014	6811.804
1992	4317.744	6479.183	7386.348	7289.733

Summary for ETS model of Time Series ID: 1080

ETS(M,A,A)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.8932

beta = 3e-04

gamma = 1e-04

Initial states:

l = 1702.8136

b = 45.1591

s = -88.1484 150.3706 -65.4593 3.2371

sigma: 0.0327

AIC	AICc	BIC
564.9718	570.2659	581.0295

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	1.924115	79.76684	60.79667	-0.07063202	2.307734	0.2906255

ACF1

Training set 0.01602256

Forecasts for Time Series ID: 1080

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3812.271	3788.730	4049.744	3856.438
1992	3993.001	3969.459	4230.473	4037.167

Summary for ETS model of Time Series ID: 1081

ETS(M,A,A)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.9995

beta = 0.0023

gamma = 5e-04

Initial states:

l = 1888.563

```
b = 33.4094
s = 23.1438 72.1365 19.1813 -114.4617
```

```
sigma: 0.0367
```

```
      AIC      AICc      BIC
573.9439 579.2380 590.0016
```

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	6.871634	87.69787	72.47985	0.0985388	2.795652	0.3436913	0.03455427

Forecasts for Time Series ID: 1081

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3573.155	3740.908	3827.907	3813.060
1992	3709.515	3877.268	3964.267	3949.420

Summary for ETS model of Time Series ID: 1082

ETS(M,A,M)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.2422
```

```
beta  = 0.1704
```

```
gamma = 1e-04
```

Initial states:

```
l = 2377.951
```

b = 43.3423

s = 1.0487 1.0225 0.9867 0.9422

sigma: 0.0115

AIC	AICc	BIC
496.4660	501.7601	512.5237

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	5.931956	35.78694	27.19905	0.1352203	0.8152402	0.1353752

ACF1

Training set 0.03258457

Forecasts for Time Series ID: 1082

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4419.810	4715.005	4976.054	5195.337
1992	4750.457	5061.260	5334.891	5563.353

Summary for ETS model of Time Series ID: 1083

ETS(A,A,A)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.7499

beta = 1e-04

gamma = 1e-04

Initial states:

l = 3242.0501

b = 21.9246

s = 358.7389 11.5206 -75.322 -294.9374

sigma: 49.1107

	AIC	AICc	BIC
	518.3536	523.6477	534.4113

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-0.71843	44.42229	35.77698	-0.05405098	1.01324	0.3750876

ACF1

Training set 0.01346436

Forecasts for Time Series ID: 1083

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3909.280	4150.809	4259.578	4628.720
1992	3996.966	4238.495	4347.263	4716.405

Summary for ETS model of Time Series ID: 1084

ETS(M,Ad,M)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.5373

beta = 1e-04

```
gamma = 0.4627
phi    = 0.9785
```

Initial states:

```
l = 5267.0428
b = 29.8147
s = 0.9979 1.0024 1.0012 0.9985
```

```
sigma: 0.0066
```

```
      AIC      AICc      BIC
496.2161 502.8828 514.0580
```

Training set error measures:

```
              ME      RMSE      MAE      MPE      MAPE      MASE
Training set 0.2210335 34.24906 26.10674 -0.0004569279 0.4508537 0.33851
              ACF1
Training set 0.1174297
```

Forecasts for Time Series ID: 1084

```
      Qtr1      Qtr2      Qtr3      Qtr4
1991 6017.635 6122.609 6168.815 6238.147
1992 6060.471 6165.179 6210.712 6279.535
```

Summary for ETS model of Time Series ID: 1085

ETS(M,N,A)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.6737

gamma = 0.3262

Initial states:

l = 3710.5868

s = 484.3356 565.1373 5.645 -1055.118

sigma: 0.032

	AIC	AICc	BIC
	593.9074	597.0185	606.3967

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	29.94298	114.2241	90.80994	0.5460934	2.387981	0.5334818

ACF1

Training set -0.09014681

Forecasts for Time Series ID: 1085

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3471.412	4818.536	5269.658	5263.200
1992	3471.412	4818.536	5269.658	5263.200

Summary for ETS model of Time Series ID: 1086

ETS(M,A,A)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.643

beta = 0.0648

gamma = 1e-04

Initial states:

l = 4896.746

b = 71.0695

s = -179.8399 385.6297 -140.4148 -65.3751

sigma: 0.0325

	AIC	AICc	BIC
	642.5128	647.8069	658.5705

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	24.36184	185.2628	154.5381	0.2332154	2.462462	0.4272918

ACF1

Training set -0.05958893

Forecasts for Time Series ID: 1086

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8624.299	8689.806	9356.371	8931.480
1992	9186.444	9251.951	9918.516	9493.625

Summary for ETS model of Time Series ID: 1087

ETS(M,N,M)

Call:



```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.9718
```

```
gamma = 1e-04
```

Initial states:

```
l = 2247.14
```

```
s = 1.0316 1.017 1.0128 0.9386
```

```
sigma: 0.0359
```

	AIC	AICc	BIC
	568.8118	571.9229	581.3012

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	28.33023	86.55504	70.95904	0.9519572	2.770329	0.4621504

	ACF1
Training set	-0.04948401

Forecasts for Time Series ID: 1087

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3245.251	3501.777	3516.239	3566.816
1992	3245.251	3501.777	3516.240	3566.816

Summary for ETS model of Time Series ID: 1088

ETS(M,A,A)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.4886
```

```
beta  = 0.1301
```

```
gamma = 7e-04
```

Initial states:

```
l = 5853.8937
```

```
b = 14.4051
```

```
s = 389.1755 194.7335 -97.6995 -486.2096
```

```
sigma: 0.0101
```

	AIC	AICc	BIC
	541.1466	546.4407	557.2043

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	10.79743	57.72596	47.44919	0.1542899	0.7493555	0.3252406

ACF1

Training set -0.006368703

Forecasts for Time Series ID: 1088

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6944.965	7409.671	7778.381	8049.040
1992	7249.731	7714.437	8083.147	8353.806

Summary for ETS model of Time Series ID: 1089

ETS(M,A,A)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.6226
```

```
beta  = 0.2092
```

```
gamma = 0.1807
```

Initial states:

```
l = 4029.6353
```

```
b = 95.1436
```

```
s = -84.3884 -2.0277 24.5541 61.862
```

```
sigma: 0.0075
```

	AIC	AICc	BIC
	499.0721	504.3663	515.1299

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-4.717637	36.10199	26.61701	-0.1052447	0.5034983	0.1484599

ACF1

Training set 0.1097611

Forecasts for Time Series ID: 1089

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6207.947	6264.001	6235.035	6256.693
1992	6414.821	6470.875	6441.909	6463.567

Summary for ETS model of Time Series ID: 1090

ETS(M,Ad,M)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.7471

beta = 1e-04

gamma = 1e-04

phi = 0.98

Initial states:

l = 4017.1269

b = 85.0048

s = 0.9503 0.994 0.986 1.0697

sigma: 0.0091

	AIC	AICc	BIC
	518.9016	525.5683	536.7435

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	5.546327	46.4525	34.6547	0.07613405	0.6244027	0.1442743	0.03733428

Forecasts for Time Series ID: 1090

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7152.494	6626.761	6713.713	6449.995
1992	7294.786	6755.299	6840.698	6568.973

Summary for ETS model of Time Series ID: 1091

ETS(M,Ad,A)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.559

beta = 0.1072

gamma = 1e-04

phi = 0.9799

Initial states:

l = 4121.9491

b = 72.548

s = -61.1023 8.9406 62.0423 -9.8807

sigma: 0.008

	AIC	AICc	BIC
	504.8616	511.5283	522.7035

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	2.12016	38.16251	26.98257	0.02549205	0.5138618	0.1548386

ACF1

Training set -0.1619771

Forecasts for Time Series ID: 1091

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6113.074	6226.800	6214.665	6184.771
1992	6275.327	6385.799	6370.475	6337.456

Summary for ETS model of Time Series ID: 1092  
ETS(M,Ad,M)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.7149
beta  = 1e-04
gamma = 0.2851
phi   = 0.9544
```

Initial states:

```
l = 4465.8572
b = 58.8816
s = 1.0023 0.9907 1.0007 1.0063
```

sigma: 0.0136

	AIC	AICc	BIC
	550.1664	556.8330	568.0083

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-1.364126	62.50463	51.63617	-0.03918484	1.004489	0.3789811
	ACF1					

Training set 0.02925251

Forecasts for Time Series ID: 1092

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5633.523	5449.081	5491.340	5464.398
1992	5661.280	5474.681	5515.940	5487.743

Summary for ETS model of Time Series ID: 1093

ETS(M,Ad,M)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.999

beta = 0.0577

gamma = 9e-04

phi = 0.9469

Initial states:

l = 4504.1432

b = 75.8984

s = 0.9793 1.0127 0.9958 1.0123

sigma: 0.0183

AIC	AICc	BIC
575.0270	581.6937	592.8689

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-5.449743	80.13855	60.35934	-0.1210796	1.217747	0.3502645

ACF1

Training set 0.1325939

Forecasts for Time Series ID: 1093

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5326.879	5246.160	5341.142	5170.213
1992	5349.608	5267.332	5361.531	5188.883

Summary for ETS model of Time Series ID: 1094

ETS(A,Ad,A)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.0213

beta = 2e-04

gamma = 1e-04

phi = 0.9784

Initial states:

l = 4095.8717

b = 75.8935

s = -69.9581 -56.0878 14.7504 111.2956

sigma: 47.9863

AIC	AICc	BIC
-----	------	-----



517.0760 523.7426 534.9179

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-3.600884	42.79818	33.52537	-0.08709027	0.6229974	0.1723558
ACF1						

Training set 0.303078

Forecasts for Time Series ID: 1094

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6355.198	6286.486	6242.881	6255.648
1992	6462.960	6391.925	6346.046	6356.588

Summary for ETS model of Time Series ID: 1095

ETS(M,A,M)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.398

beta = 0.398

gamma = 1e-04

Initial states:

l = 2617.4518

b = 45.1709

s = 1.0512 0.9613 1.0301 0.9574

sigma: 0.0107

AIC	AICc	BIC
496.1205	501.4146	512.1782

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	3.009087	35.98211	27.3833	0.06263172	0.7595088	0.1388355

ACF1

Training set -0.08659791

Forecasts for Time Series ID: 1095

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4717.478	5174.995	4922.527	5484.373
1992	5087.993	5573.617	5294.538	5891.159

Summary for ETS model of Time Series ID: 1096

ETS(M,A,M)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.4945

beta = 1e-04

gamma = 1e-04

Initial states:

l = 2305.2421

b = 50.6527

s = 1.0522 1.2401 0.853 0.8547

sigma: 0.0552

AIC	AICc	BIC
632.8530	638.1471	648.9107

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	17.17658	160.1584	122.1765	0.09841051	3.841434	0.4401132

ACF1

Training set -0.09614029

Forecasts for Time Series ID: 1096

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4258.048	4292.556	6303.632	5402.045
1992	4431.501	4465.653	6555.287	5615.576

Summary for ETS model of Time Series ID: 1097

ETS(M,Ad,M)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

alpha = 0.308

beta = 0.308

gamma = 0.6895

phi = 0.98

Initial states:

```
l = 2716.8609
b = 81.7203
s = 0.9878 1.0079 1.0195 0.9847
```

```
sigma: 0.0062
```

```
      AIC      AICc      BIC
461.6466 468.3133 479.4885
```

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	4.347336	22.8431	18.57441	0.08672987	0.4525664	0.0725648	0.1832684

Forecasts for Time Series ID: 1097

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5497.854	5825.397	5926.337	5928.330
1992	5810.074	6144.937	6240.485	6232.160

Summary for ETS model of Time Series ID: 1098

ETS(M,A,A)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.3723
```

```
beta  = 6e-04
```

```
gamma = 0.6277
```

Initial states:

```
l = 3180.4302
b = 68.1737
s = 375.3964 -168.6716 -133.3057 -73.4191
```

```
sigma: 0.0253
```

```
      AIC      AICc      BIC
592.3488 597.6429 608.4065
```

Training set error measures:

```
              ME      RMSE      MAE      MPE      MAPE      MASE
Training set -0.01726335 109.2853 85.39705 -0.09708652 1.854214 0.3163908
```

```
      ACF1
Training set 0.1439441
```

Forecasts for Time Series ID: 1098

```
      Qtr1      Qtr2      Qtr3      Qtr4
1991 6048.888 6243.274 6192.496 6889.292
1992 6321.581 6515.967 6465.189 7161.985
```

Summary for ETS model of Time Series ID: 1099

ETS(M,A,M)

Call:

```
ets(y = train_data)
```

Smoothing parameters:

```
alpha = 0.2422
beta  = 0.1704
gamma = 1e-04
```

Initial states:

l = 2377.951

b = 43.3423

s = 1.0487 1.0225 0.9867 0.9422

sigma: 0.0115

	AIC	AICc	BIC
	496.4660	501.7601	512.5237

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	5.931956	35.78694	27.19905	0.1352203	0.8152402	0.1353752

	ACF1
Training set	0.03258457

Forecasts for Time Series ID: 1099

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4419.810	4715.005	4976.054	5195.337
1992	4750.457	5061.260	5334.891	5563.353

Summary for ETS model of Time Series ID: 1100

ETS(M,N,M)

Call:

ets(y = train\_data)

Smoothing parameters:

alpha = 0.3675

gamma = 0.0038

Initial states:

l = 5463.5524

s = 1.3718 1.1295 0.7902 0.7085

sigma: 0.0507

	AIC	AICc	BIC
	667.5577	670.6688	680.0470

Training set error measures:

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	27.61646	303.1197	199.3364	0.3470265	3.394563	0.6703201

ACF1

Training set -0.05240952

Forecasts for Time Series ID: 1100

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4213.595	4699.284	6717.163	8157.150
1992	4213.610	4699.301	6717.187	8157.179

8.38 Code computing the average Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (sMAPE) for the ETS models and comparing its performance with the Theta and Damped Exponential Smoothing models, which serve as benchmarks (benchmark models fitted in Appendix 8.37)

```
# Calculate average MAPE and sMAPE for each method
avg_mape_ets <- mean(mape_ets, na.rm = TRUE)
avg_smape_ets <- mean(smape_ets, na.rm = TRUE)
avg_mape_theta <- mean(mape_theta, na.rm = TRUE)
avg_smape_theta <- mean(smape_theta, na.rm = TRUE)
avg_mape_damped <- mean(mape_damped, na.rm = TRUE)
avg_smape_damped <- mean(smape_damped, na.rm = TRUE)

# Store evaluation metrics for each model in a data frame
ets_batch_evaluation_metrics <- data.frame(
  Model = c("ETS", "Theta", "Damped Exponential Smoothing"),
  MAPE = c(avg_mape_ets, avg_mape_theta, avg_mape_damped),
  sMAPE = c(avg_smape_ets, avg_smape_theta, avg_smape_damped)
)

# Print the evaluation metrics for comparison
cat("Table 20: Error measures evaluating automatic ETS model's
    out-of-sample accuracy")
print(ets_batch_evaluation_metrics, row.names = FALSE)

# Select the model with the lowest values for MAPE
```



```

ets_batch_best_model_mape <- ets_batch_evaluation_metrics[which.min(
  ets_batch_evaluation_metrics$MAPE), ]

# Select the model with the lowest values for sMAPE
ets_batch_best_model_smape <- ets_batch_evaluation_metrics[which.min(
  ets_batch_evaluation_metrics$sMAPE), ]

# Print the best model
cat("Best model based on MAPE:", ets_batch_best_model_mape$Model, "\n")
cat("Best model based on sMAPE:", ets_batch_best_model_smape$Model, "\n")

```

**8.39** Code printing summaries of automatically fitted TBATS models for each series (IDs 1001 to 1100) and printing respective forecasted values.

```

# Define the series IDs and criterion
ts_start <- 1001
ts_end <- 1100
criterion <- "aicc"
num_ts <- ts_end - ts_start + 1

# Initialize arrays to store MAPE and sMAPE for TBATS and benchmarks
mape_tbats <- numeric(num_ts)
mape_theta <- numeric(num_ts)
mape_damped <- numeric(num_ts)
smape_tbats <- numeric(num_ts)
smape_theta <- numeric(num_ts)
smape_damped <- numeric(num_ts)

```

```

# Loop through each time series
for (s in ts_start:ts_end) {
  train_data <- M3[[s]]$x
  test_data <- M3[[s]]$xx
  h <- length(test_data)

  # Fit TBATS model
  tbats_fit <- tbats(train_data)
  # Print summary of the fitted TBATS model
  cat("Summary for TBATS model of Time Series ID:", s, "\n")
  print(summary(tbats_fit))
  cat("\n") # Add a newline after each summary
  tbats_fcst <- forecast(tbats_fit, h = h)$mean
  # Print forecasts
  cat("Forecasts for Time Series ID:", s, "\n")
  print(tbats_fcst)
  cat("\n") # Add a newline after printing forecasts

  # Calculate MAPE for TBATS
  mape_tbats[s - ts_start + 1] <- 100 * mean(abs(test_data - tbats_fcst) /
                                             test_data, na.rm = TRUE)

  # Calculate sMAPE for TBATS
  smape_tbats[s - ts_start + 1] <- 200 * mean(abs(test_data - tbats_fcst) /
                                             (abs(test_data) + abs(tbats_fcst)),
                                             na.rm = TRUE)

  # Fit Theta model
  theta_fit <- thetaf(train_data)
  # Print summary of the fitted Theta model

```

```

#cat("Summary for Theta model of Time Series ID:", s, "\n")
#print(summary(theta_fit))
#cat("\n") # Add a newline after each summary
theta_fcst <- forecast(theta_fit, h = h)$mean
# Print forecasts
#cat("Forecasts for Time Series ID:", s, "\n")
#print(theta_fcst)
#cat("\n") # Add a newline after printing forecasts

# Calculate MAPE for Theta
mape_theta[s - ts_start + 1] <- 100 * mean(abs(test_data - theta_fcst) /
                                           test_data, na.rm = TRUE)

# Calculate sMAPE for Theta
smape_theta[s - ts_start + 1] <- 200 * mean(abs(test_data - theta_fcst) /
                                           (abs(test_data) + abs(theta_fcst)),
                                           na.rm = TRUE)

# Fit Damped Exponential Smoothing model
tryCatch({
  damped_model <- ets(train_data, model = "ZZZ", damped = TRUE)
  damped_fcst <- forecast(damped_model, h = h)$mean
  # Calculate MAPE for Damped Exponential Smoothing
  mape_damped[s - ts_start + 1] <- 100 * mean(abs(test_data - damped_fcst) /
                                              test_data, na.rm = TRUE)

  # Calculate sMAPE for Damped Exponential Smoothing
  smape_damped[s - ts_start + 1] <- 200 * mean(abs(test_data - damped_fcst) /
                                              (abs(test_data) + abs(damped_fcst)),
                                              na.rm = TRUE)

}, error = function(e) {

```

```

    mape_damped[s - ts_start + 1] <- NA # Assign NA in case of error
    smape_damped[s - ts_start + 1] <- NA # Assign NA in case of error
  })
}

```

Summary for TBATS model of Time Series ID: 1001

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1001

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7166.651	7269.799	7372.948	7476.097
1992	7579.245	7682.394	7785.542	7888.691

Summary for TBATS model of Time Series ID: 1002

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1002

Qtr1	Qtr2	Qtr3	Qtr4
------	------	------	------

1991 6754.523 6841.132 6927.741 7014.350  
 1992 7100.960 7187.569 7274.178 7360.787

Summary for TBATS model of Time Series ID: 1003

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1003

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6685.525	6685.525	6685.525	6685.525

1992 6685.525 6685.525 6685.525 6685.525

Summary for TBATS model of Time Series ID: 1004

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1004

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5933.716	5976.238	6018.585	6060.758
1992	6102.758	6144.585	6186.240	6227.724

Summary for TBATS model of Time Series ID: 1005

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1005

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5725.946	5690.273	5661.735	5638.904
1992	5620.639	5606.028	5594.339	5584.987



Summary for TBATS model of Time Series ID: 1006

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1006

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5980.048	5980.048	5980.048	5980.048
1992	5980.048	5980.048	5980.048	5980.048

Summary for TBATS model of Time Series ID: 1007

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	1	-none-	numeric
ma.coefficients	2	-none-	numeric
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	4	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	176	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1007

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8557.739	8644.644	8742.101	8828.593
1992	8905.352	8973.474	9033.931	9087.585

Summary for TBATS model of Time Series ID: 1008

	Length	Class	Mode
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lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1008

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6270.826	6367.620	6465.905	6565.702
1992	6667.034	6769.927	6874.403	6980.486

Summary for TBATS model of Time Series ID: 1009

	Length	Class	Mode
lambda	1	-none-	numeric

alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1009

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6912.748	6912.748	6912.748	6912.748
1992	6912.748	6912.748	6912.748	6912.748

Summary for TBATS model of Time Series ID: 1010

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric

beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1010

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6849.801	6779.253	6722.815	6677.665
1992	6641.544	6612.648	6589.531	6571.037

Summary for TBATS model of Time Series ID: 1011

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric

damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	16	ts	numeric
errors	16	ts	numeric
x	32	-none-	numeric
seasonal.periods	0	-none-	NULL
y	16	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1011

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5793.364	5834.437	5875.510	5916.584
1992	5957.657	5998.731	6039.804	6080.877

Summary for TBATS model of Time Series ID: 1012

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric

gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1012

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6994.008	6768.827	6545.474	6323.981
1992	6104.380	5886.707	5670.996	5457.286

Summary for TBATS model of Time Series ID: 1013

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric

gamma.two.values	1	-none-	numeric
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	4	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	176	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1013

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7485.150	7501.067	7574.626	7753.795
1992	7875.322	7891.240	7964.799	8143.967

Summary for TBATS model of Time Series ID: 1014

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric



beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1014

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7578.990	7842.703	8113.929	8392.834
1992	8679.588	8974.364	9277.337	9588.685

Summary for TBATS model of Time Series ID: 1015

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric

damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1015

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7184.269	7289.161	7394.052	7498.944
1992	7603.836	7708.728	7813.620	7918.512

Summary for TBATS model of Time Series ID: 1016

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric

gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1016

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9019.896	8934.411	8866.606	8812.731
1992	8769.867	8735.725	8708.507	8686.794

Summary for TBATS model of Time Series ID: 1017

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL

ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1017

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6525.453	6525.453	6525.453	6525.453
1992	6525.453	6525.453	6525.453	6525.453

Summary for TBATS model of Time Series ID: 1018

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL

ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

#### Forecasts for Time Series ID: 1018

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5149.318	5149.318	5149.318	5149.318
1992	5149.318	5149.318	5149.318	5149.318

#### Summary for TBATS model of Time Series ID: 1019

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL

likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1019

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6182.786	6182.786	6182.786	6182.786
1992	6182.786	6182.786	6182.786	6182.786

Summary for TBATS model of Time Series ID: 1020

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric

optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1020

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6300.322	6312.004	6323.687	6335.369
1992	6347.051	6358.733	6370.416	6382.098

Summary for TBATS model of Time Series ID: 1021

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric

variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1021

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6855.378	6855.378	6855.378	6855.378
1992	6855.378	6855.378	6855.378	6855.378

Summary for TBATS model of Time Series ID: 1022

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric



AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1022

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6068.451	6068.451	6068.451	6068.451
1992	6068.451	6068.451	6068.451	6068.451

Summary for TBATS model of Time Series ID: 1023

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric

parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1023

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8432.281	8582.437	8733.394	8885.147
1992	9037.690	9191.018	9345.125	9500.007

Summary for TBATS model of Time Series ID: 1024

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list

seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1024

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4243.675	4321.433	4400.552	4481.054
1992	4562.962	4646.300	4731.092	4817.362

Summary for TBATS model of Time Series ID: 1025

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	2	-none-	numeric
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	4	-none-	numeric

fitted.values	44	ts	numeric
errors	44	ts	numeric
x	176	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1025

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8264.474	8204.669	8352.097	8487.434
1992	8622.770	8758.107	8893.443	9028.779

Summary for TBATS model of Time Series ID: 1026

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric

errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1026

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8395.712	8548.943	8704.971	8863.846
1992	9025.622	9190.349	9358.084	9528.879

Summary for TBATS model of Time Series ID: 1027

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric

x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

#### Forecasts for Time Series ID: 1027

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9761.509	9988.383	10219.615	10455.274
1992	10695.425	10940.136	11189.477	11443.516

#### Summary for TBATS model of Time Series ID: 1028

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric

seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

#### Forecasts for Time Series ID: 1028

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5449.988	5483.215	5516.442	5549.669
1992	5582.896	5616.123	5649.350	5682.577

#### Summary for TBATS model of Time Series ID: 1029

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL

y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1029

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8040.555	8103.474	8166.392	8229.310
1992	8292.228	8355.147	8418.065	8480.983

Summary for TBATS model of Time Series ID: 1030

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric



call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1030

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4115.292	4115.292	4115.292	4115.292
1992	4115.292	4115.292	4115.292	4115.292

Summary for TBATS model of Time Series ID: 1031

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call

series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1031

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8136.079	8136.079	8136.079	8136.079
1992	8136.079	8136.079	8136.079	8136.079

Summary for TBATS model of Time Series ID: 1032

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character

method	1	-none-	character
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Forecasts for Time Series ID: 1032

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7874.983	7996.430	8119.745	8244.957
1992	8372.093	8501.185	8632.261	8765.353

Summary for TBATS model of Time Series ID: 1033

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1033

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9282.714	9332.451	9382.188	9431.925
1992	9481.661	9531.398	9581.135	9630.872

Summary for TBATS model of Time Series ID: 1034

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1034

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5288.286	5330.189	5371.308	5411.658
1992	5451.253	5490.107	5528.235	5565.649

Summary for TBATS model of Time Series ID: 1035

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1035

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5137.827	5205.842	5274.102	5342.605
1992	5411.351	5480.337	5549.563	5619.027

Summary for TBATS model of Time Series ID: 1036

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1036

Qtr1	Qtr2	Qtr3	Qtr4
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1991 5046.507 5096.004 5145.986 5196.458  
 1992 5247.425 5298.892 5350.864 5403.346

Summary for TBATS model of Time Series ID: 1037

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1037

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5326.834	5379.380	5432.443	5486.031

1992 5540.146 5594.796 5649.985 5705.718

Summary for TBATS model of Time Series ID: 1038

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1038

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4921.559	5004.431	5087.302	5170.173
1992	5253.044	5335.915	5418.786	5501.658



Summary for TBATS model of Time Series ID: 1039

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1039

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7238.655	7297.525	7356.396	7415.267
1992	7474.137	7533.008	7591.879	7650.749

Summary for TBATS model of Time Series ID: 1040

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1040

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5775.699	5915.049	6056.980	6201.519
1992	6348.697	6498.542	6651.083	6806.349

Summary for TBATS model of Time Series ID: 1041

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1041

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9761.509	9988.383	10219.615	10455.274
1992	10695.425	10940.136	11189.477	11443.516

Summary for TBATS model of Time Series ID: 1042

Length	Class	Mode
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lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1042

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5678.516	5678.516	5678.516	5678.516
1992	5678.516	5678.516	5678.516	5678.516

Summary for TBATS model of Time Series ID: 1043

	Length	Class	Mode
lambda	1	-none-	numeric

alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1043

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9464.080	9678.341	9896.438	10118.423
1992	10344.347	10574.260	10808.217	11046.268

Summary for TBATS model of Time Series ID: 1044

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric

beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1044

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9761.509	9988.383	10219.615	10455.274
1992	10695.425	10940.136	11189.477	11443.516

Summary for TBATS model of Time Series ID: 1045

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL

damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1045

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7310.578	7310.578	7310.578	7310.578
1992	7310.578	7310.578	7310.578	7310.578

Summary for TBATS model of Time Series ID: 1046

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric

gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1046

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8912.013	8958.282	9004.552	9050.821
1992	9097.091	9143.360	9189.629	9235.899

Summary for TBATS model of Time Series ID: 1047

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL



ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1047

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9282.714	9332.451	9382.188	9431.925
1992	9481.661	9531.398	9581.135	9630.872

Summary for TBATS model of Time Series ID: 1048

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL

ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1048

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7322.682	7396.406	7470.129	7543.852
1992	7617.576	7691.299	7765.022	7838.745

Summary for TBATS model of Time Series ID: 1049

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	0	-none-	NULL

ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	4	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	176	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1049

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3503.373	3175.553	3778.166	4215.064
1992	3677.838	3344.838	3956.724	4399.731

Summary for TBATS model of Time Series ID: 1050

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric

gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1050

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4186.779	4250.954	4316.114	4382.272
1992	4449.445	4517.647	4586.895	4657.204

Summary for TBATS model of Time Series ID: 1051

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL

ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1051

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3840.012	3909.152	3979.463	4050.963
1992	4123.673	4197.610	4272.794	4349.246

Summary for TBATS model of Time Series ID: 1052

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL

ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1052

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4243.675	4321.433	4400.552	4481.054
1992	4562.962	4646.300	4731.092	4817.362

Summary for TBATS model of Time Series ID: 1053

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL

likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1053

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4326.280	4306.871	4291.344	4278.922
1992	4268.984	4261.034	4254.674	4249.586

Summary for TBATS model of Time Series ID: 1054

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric

optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1054

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7692.103	7809.855	7928.196	8047.124
1992	8166.635	8286.727	8407.397	8528.642

Summary for TBATS model of Time Series ID: 1055

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric



variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1055

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6624.748	6744.717	6866.741	6990.854
1992	7117.090	7245.482	7376.065	7508.875

Summary for TBATS model of Time Series ID: 1056

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric

AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1056

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5911.252	5833.384	5771.815	5723.020
1992	5684.275	5653.465	5628.935	5609.386

Summary for TBATS model of Time Series ID: 1057

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric

parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1057

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7960.137	8031.037	8101.937	8172.838
1992	8243.738	8314.638	8385.539	8456.439

Summary for TBATS model of Time Series ID: 1058

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list

seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1058

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4036.701	4036.701	4036.701	4036.701
1992	4036.701	4036.701	4036.701	4036.701

Summary for TBATS model of Time Series ID: 1059

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric

fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1059

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3726.979	3726.979	3726.979	3726.979
1992	3726.979	3726.979	3726.979	3726.979

Summary for TBATS model of Time Series ID: 1060

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric

errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1060

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4115.292	4115.292	4115.292	4115.292
1992	4115.292	4115.292	4115.292	4115.292

Summary for TBATS model of Time Series ID: 1061

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric

x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

#### Forecasts for Time Series ID: 1061

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4194.267	4194.267	4194.267	4194.267
1992	4194.267	4194.267	4194.267	4194.267

#### Summary for TBATS model of Time Series ID: 1062

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric

seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1062

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7399.993	7399.993	7399.993	7399.993
1992	7399.993	7399.993	7399.993	7399.993

Summary for TBATS model of Time Series ID: 1063

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL



y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1063

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6371.639	6371.639	6371.639	6371.639
1992	6371.639	6371.639	6371.639	6371.639

Summary for TBATS model of Time Series ID: 1064

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric

call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1064

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6996.397	6996.397	6996.397	6996.397
1992	6996.397	6996.397	6996.397	6996.397

Summary for TBATS model of Time Series ID: 1065

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	44	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call

series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1065

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7816.674	7816.674	7816.674	7816.674
1992	7816.674	7816.674	7816.674	7816.674

Summary for TBATS model of Time Series ID: 1066

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character

method	1	-none-	character
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Forecasts for Time Series ID: 1066

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6067.446	6175.040	6283.599	6393.122
1992	6503.611	6615.066	6727.487	6840.874

Summary for TBATS model of Time Series ID: 1067

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1067

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6397.048	6431.016	6465.162	6499.489
1992	6533.996	6568.686	6603.558	6638.614

Summary for TBATS model of Time Series ID: 1068

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1068

	Qtr1	Qtr2	Qtr3	Qtr4
1991	9004.831	9210.121	9418.864	9631.100
1992	9846.866	10066.200	10289.140	10515.726

Summary for TBATS model of Time Series ID: 1069

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1069

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7297.530	7407.901	7518.272	7628.643
1992	7739.015	7849.386	7959.757	8070.129

Summary for TBATS model of Time Series ID: 1070

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1070

Qtr1	Qtr2	Qtr3	Qtr4
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1991	9103.709	9317.681	9534.758	9754.960
1992	9978.303	10204.804	10434.482	10667.354

Summary for TBATS model of Time Series ID: 1071

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	26	ts	numeric
errors	26	ts	numeric
x	52	-none-	numeric
seasonal.periods	0	-none-	NULL
y	26	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1071

	Qtr1	Qtr2	Qtr3	Qtr4
1992			5755.802	5777.295



1993 5798.787 5820.280 5841.772 5863.265  
 1994 5884.757 5906.250

Summary for TBATS model of Time Series ID: 1072

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	1	-none-	numeric
fitted.values	26	ts	numeric
errors	26	ts	numeric
x	26	-none-	numeric
seasonal.periods	0	-none-	NULL
y	26	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1072

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6165.575	6165.575	6165.575	6165.575

1992 6165.575 6165.575 6165.575 6165.575

Summary for TBATS model of Time Series ID: 1073

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	26	ts	numeric
errors	26	ts	numeric
x	52	-none-	numeric
seasonal.periods	0	-none-	NULL
y	26	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1073

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8142.181	8197.062	8251.944	8306.825
1992	8361.706	8416.588	8471.469	8526.351

Summary for TBATS model of Time Series ID: 1074

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	26	ts	numeric
errors	26	ts	numeric
x	52	-none-	numeric
seasonal.periods	0	-none-	NULL
y	26	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1074

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7092.660	7103.209	7113.757	7124.306
1992	7134.855	7145.403	7155.952	7166.500

Summary for TBATS model of Time Series ID: 1075

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	26	ts	numeric
errors	26	ts	numeric
x	52	-none-	numeric
seasonal.periods	0	-none-	NULL
y	26	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1075

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8377.703	8347.461	8319.997	8295.054
1992	8272.401	8251.828	8233.145	8216.177

Summary for TBATS model of Time Series ID: 1076

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	2	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	88	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1076

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5449.988	5483.215	5516.442	5549.669
1992	5582.896	5616.123	5649.350	5682.577

Summary for TBATS model of Time Series ID: 1077

Length	Class	Mode
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lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	3	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	7	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	308	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1077

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4871.621	5233.788	5391.760	5888.971
1992	5222.137	5576.770	5754.971	6264.671

# Summary for TBATS model of Time Series ID: 1078

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	2	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	6	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	264	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

## Forecasts for Time Series ID: 1078

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8639.363	8191.158	8415.513	8202.764
1992	9006.115	8579.445	8785.723	8594.005

Summary for TBATS model of Time Series ID: 1079

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	3	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	7	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	308	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character



method	1	-none-	character
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Forecasts for Time Series ID: 1079

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3999.341	6094.920	6921.117	6902.875
1992	4367.765	6598.574	7541.595	7463.236

Summary for TBATS model of Time Series ID: 1080

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	3	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	7	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	308	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric

q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1080

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3810.199	3927.520	4166.715	4175.956
1992	4329.984	4511.202	4783.590	4844.752

Summary for TBATS model of Time Series ID: 1081

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	4	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	176	-none-	numeric
seasonal.periods	1	-none-	numeric

k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1081

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3585.769	3752.103	3919.331	3845.742
1992	3775.997	3946.961	4118.749	4043.164

Summary for TBATS model of Time Series ID: 1082

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	3	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	7	-none-	numeric
fitted.values	44	ts	numeric

errors	44	ts	numeric
x	308	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1082

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4416.318	4728.525	4990.714	5226.756
1992	4786.660	5103.624	5383.298	5622.909

Summary for TBATS model of Time Series ID: 1083

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	3	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric

parameters	2	-none-	list
seed.states	7	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	308	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1083

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3933.468	4189.520	4417.470	4817.803
1992	4180.502	4421.628	4654.533	5048.703

Summary for TBATS model of Time Series ID: 1084

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric

optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	4	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	176	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1084

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6085.388	6096.665	6151.292	6159.338
1992	6123.428	6133.733	6187.669	6194.767

Summary for TBATS model of Time Series ID: 1085

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric

ar.coefficients	2	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	5	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	220	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1085

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3660.583	4931.238	5509.993	5506.931
1992	3924.666	5170.168	5768.871	5741.156

Summary for TBATS model of Time Series ID: 1086

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric

damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	2	-none-	numeric
ma.coefficients	1	-none-	numeric
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	7	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	308	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1086

	Qtr1	Qtr2	Qtr3	Qtr4
1991	8407.512	8692.011	9022.769	8837.086
1992	8743.720	9029.053	9346.274	9161.156

Summary for TBATS model of Time Series ID: 1087

Length	Class	Mode
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lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	1	-none-	numeric
ma.coefficients	2	-none-	numeric
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	7	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	308	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1087

	Qtr1	Qtr2	Qtr3	Qtr4
1991	3352.503	3635.732	3709.391	3823.620
1992	3581.026	3912.837	3998.572	4115.010

Summary for TBATS model of Time Series ID: 1088

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	3	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	7	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	308	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1088

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6911.932	7423.467	7751.342	8056.950
1992	7225.932	7703.242	8066.903	8341.466

Summary for TBATS model of Time Series ID: 1089

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	1	-none-	numeric
ma.coefficients	2	-none-	numeric
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	7	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	308	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character

method	1	-none-	character
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Forecasts for Time Series ID: 1089

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6155.309	6196.038	6131.229	6147.533
1992	6238.615	6278.672	6212.622	6225.861

Summary for TBATS model of Time Series ID: 1090

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	2	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	6	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	264	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric

q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1090

	Qtr1	Qtr2	Qtr3	Qtr4
1991	7173.648	6633.571	6791.136	6510.086
1992	7363.966	6837.848	6967.179	6705.098

Summary for TBATS model of Time Series ID: 1091

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	4	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	176	-none-	numeric
seasonal.periods	1	-none-	numeric

k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1091

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6110.406	6222.704	6214.944	6185.332
1992	6273.725	6381.972	6370.263	6336.798

Summary for TBATS model of Time Series ID: 1092

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	2	-none-	numeric
ma.coefficients	1	-none-	numeric
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	7	-none-	numeric
fitted.values	44	ts	numeric

errors	44	ts	numeric
x	308	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1092

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5604.653	5458.348	5506.747	5460.126
1992	5622.827	5479.337	5522.680	5479.038

Summary for TBATS model of Time Series ID: 1093

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.values	0	-none-	NULL
ar.coefficients	1	-none-	numeric
ma.coefficients	2	-none-	numeric
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list

seed.states	5	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	220	-none-	numeric
seasonal.periods	0	-none-	NULL
y	44	ts	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1093

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5320.757	5178.386	5341.203	5202.955
1992	5363.507	5227.612	5385.934	5252.356

Summary for TBATS model of Time Series ID: 1094

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	0	-none-	NULL
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list



seed.states	4	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	176	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1094

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6347.357	6341.503	6252.951	6320.014
1992	6468.718	6460.767	6370.155	6435.194

Summary for TBATS model of Time Series ID: 1095

	Length	Class	Mode
lambda	0	-none-	NULL
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	1	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric

variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	5	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	220	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1095

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4704.391	5148.341	4886.704	5386.580
1992	5030.803	5459.295	5212.963	5697.686

Summary for TBATS model of Time Series ID: 1096

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	2	-none-	numeric

ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	5	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	220	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1096

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4422.296	4500.155	6287.833	5656.236
1992	4586.567	4792.695	6472.086	5934.665

Summary for TBATS model of Time Series ID: 1097

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric

gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	4	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	8	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	352	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1097

	Qtr1	Qtr2	Qtr3	Qtr4
1991	5500.702	5799.474	5892.073	5898.472
1992	5795.835	6092.514	6181.815	6182.116

Summary for TBATS model of Time Series ID: 1098

	Length	Class	Mode
lambda	0	-none-	NULL

alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	2	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	6	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	264	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1098

	Qtr1	Qtr2	Qtr3	Qtr4
1991	6105.887	6313.083	6226.140	6880.892
1992	6418.057	6602.768	6531.745	7172.349

Summary for TBATS model of Time Series ID: 1099

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	1	-none-	numeric
damping.parameter	1	-none-	numeric
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	3	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	7	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	308	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1099

Qtr1	Qtr2	Qtr3	Qtr4
------	------	------	------

1991 4416.318 4728.525 4990.714 5226.756  
 1992 4786.660 5103.624 5383.298 5622.909

Summary for TBATS model of Time Series ID: 1100

	Length	Class	Mode
lambda	1	-none-	numeric
alpha	1	-none-	numeric
beta	0	-none-	NULL
damping.parameter	0	-none-	NULL
gamma.one.values	1	-none-	numeric
gamma.two.values	1	-none-	numeric
ar.coefficients	3	-none-	numeric
ma.coefficients	0	-none-	NULL
likelihood	1	-none-	numeric
optim.return.code	1	-none-	numeric
variance	1	-none-	numeric
AIC	1	-none-	numeric
parameters	2	-none-	list
seed.states	6	-none-	numeric
fitted.values	44	ts	numeric
errors	44	ts	numeric
x	264	-none-	numeric
seasonal.periods	1	-none-	numeric
k.vector	1	-none-	numeric
y	44	ts	numeric
p	1	-none-	numeric
q	1	-none-	numeric
call	2	-none-	call
series	1	-none-	character
method	1	-none-	character

Forecasts for Time Series ID: 1100

	Qtr1	Qtr2	Qtr3	Qtr4
1991	4125.187	4744.753	6675.273	8155.681
1992	4196.629	4695.554	6720.552	8071.406

**8.40** Code computing the average Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (sMAPE) for the TBATS models and comparing its performance with the Theta and Damped Exponential Smoothing models, which serve as benchmarks (benchmark models fitted in Appendix 8.39)

```
# Calculate average MAPE and sMAPE for each method
avg_mape_tbats <- mean(mape_tbats, na.rm = TRUE)
avg_smape_tbats <- mean(smape_tbats, na.rm = TRUE)
avg_mape_theta <- mean(mape_theta, na.rm = TRUE)
avg_smape_theta <- mean(smape_theta, na.rm = TRUE)
avg_mape_damped <- mean(mape_damped, na.rm = TRUE)
avg_smape_damped <- mean(smape_damped, na.rm = TRUE)

# Store evaluation metrics for each model in a data frame
tbats_batch_evaluation_metrics <- data.frame(
  Model = c("TBATS", "Theta", "Damped Exponential Smoothing"),
  MAPE = c(avg_mape_tbats, avg_mape_theta, avg_mape_damped),
  sMAPE = c(avg_smape_tbats, avg_smape_theta, avg_smape_damped)
)
```



```

# Print the evaluation metrics for comparison
cat("Table 21: Error measures evaluating automatic TBATS model's
    out-of-sample accuracy")
print(tbats_batch_evaluation_metrics, row.names = FALSE)

# Select the model with the lowest values for MAPE
tbats_batch_best_model_mape <- tbats_batch_evaluation_metrics[which.min(
    tbats_batch_evaluation_metrics$MAPE), ]

# Select the model with the lowest values for sMAPE
tbats_batch_best_model_smape <- tbats_batch_evaluation_metrics[which.min(
    tbats_batch_evaluation_metrics$sMAPE), ]

# Print the best model
cat("Best model based on MAPE:", tbats_batch_best_model_mape$Model, "\n")
cat("Best model based on sMAPE:", tbats_batch_best_model_smape$Model, "\n")

```

**8.41** Code computing the average Mean Absolute Percentage Error (MAPE) and Symmetric Mean Absolute Percentage Error (sMAPE) for all three models and comparing its performance with the Theta and Damped Exponential Smoothing models, which serve as benchmarks

```

# Store evaluation metrics for each method in a data frame
evaluation_metrics_summary <- data.frame(
  Method = c("ARIMA",
             "ETS",
             "TBATS",

```

```

        "Theta",
        "Damped Exponential Smoothing"),
MAPE = c(avg_mape_arima,
        avg_mape_ets,
        avg_mape_tbats,
        avg_mape_theta,
        avg_mape_damped),
sMAPE = c(avg_smape_arima,
        avg_smape_ets,
        avg_smape_tbats,
        avg_smape_theta,
        avg_smape_damped)
)

# Sort the data frame in ascending order based on both MAPE and sMAPE values
sorted_metrics <- evaluation_metrics_summary[order(
    evaluation_metrics_summary$MAPE, evaluation_metrics_summary$sMAPE), ]

# Print the sorted data frame
cat("Table 22: Error measures evaluating out-of-sample accuracy
    of the automatic models")
print(sorted_metrics, row.names = FALSE)

# Identify the row corresponding to the best model
best_model_row <- sorted_metrics[1, ]

# Print the best model with highlighting
cat("\nBest model based on MAPE and sMAPE:\n")
print(best_model_row, row.names = FALSE)

```