MONASH University

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Semester One 2018
Examination Period

Faculty of Business & Economics

EXAM CODES: **ETC3550**

TITLE OF PAPER: **Applied Forecasting for Business and Economics**

EXAM DURATION: 2 hours writing time

READING TIME: 10 minutes

THIS PAPER IS FOR STUDENTS STUDYING AT: (tick where applicable)

☐ Berwick	✓ Clayton	☐ Malaysia	☐ Off Campus Learning	☐ Open Learning
☐ Caulfield	☐ Gippsland	☐ Peninsula	☐ Monash Extension	☐ South Africa
☐ Parkville	☐ Other (specify)			

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Items/materials on your desk, chair, in your clothing or otherwise on your person will be deemed to be in your possession.

No examination materials are to be removed from the room. This includes retaining, copying, memorising or noting down content of exam material for personal use or to share with any other person by any means following your exam.

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AUTHORISED MATERIALS

OPEN BOOK ☐ YES ✓ NO

CALCULATORS ✓ YES ☐ NO
If YES, only a HP 10bII+ calculator is permitted

SPECIFICALLY PERMITTED ITEMS ☐ YES ✓ NO
if yes, items permitted are:

Candidates must complete this section if required to write answers within this paper

STUDENT ID: ___ ___ ___ ___ ___ ___ ___ ___ DESK NUMBER: ___ ___ ___ ___ ___ ___

The exam contains FIVE questions. ALL questions must be answered. The exam is worth 100 marks in total.

QUESTION 1

Write about a quarter of a page each on any FOUR of the following topics. (Clearly state if you agree or disagree with each statement. No marks will be given without any justification.)

(a) Prediction intervals are unnecessary because managers just want point forecasts.

(b) Whether we use a naïve approach, a decomposition, ETS or ARIMA models for forecasting, we always need to transform our data.

(c) Simple exponential smoothing should only be used for a series with a constant underlying level.

(d) All three information criteria: AIC, AICc and BIC are useful and they can potentially choose a different model. We prefer to use the AICc forecasting.

(e) The 95% prediction interval for an h-step-ahead naïve forecast is given by $\hat{y}_{T+h} \pm 1.96\sqrt{h\sigma^2}$.

(f) Regression models are not useful for forecasting because we always need to provide forecasts of the predictors.

Total: 20 marks

— END OF QUESTION 1 —

QUESTION 2

Figure 1 shows the total household expenditure for cigarette and tobacco consumption (CTC) in Victoria. The prices are represented as a chain volume measure (a representation of constant prices) in billions of dollars over the period 1985Q3–2017Q4.

Figure 1:

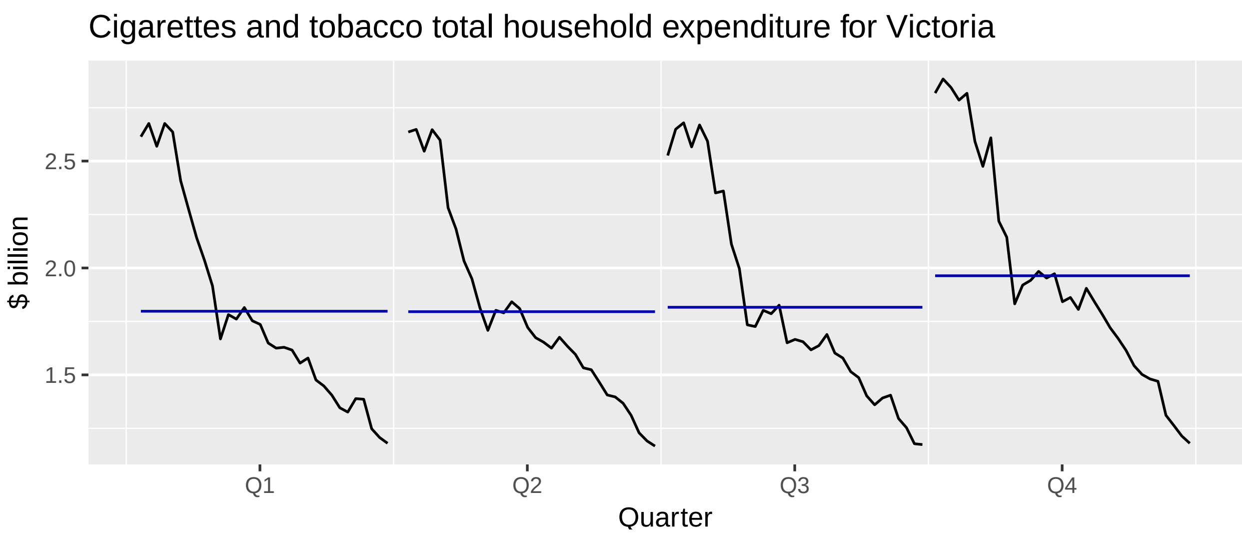

Figure 2:

(a) Describe the CTC series. Explain in detail what is plotted in Figures 1 and 2.

4 marks

(b) Do you think transforming this series will help? Why? Figure 3 shows two possible transformations. Describe what you see and which one you would prefer to use.

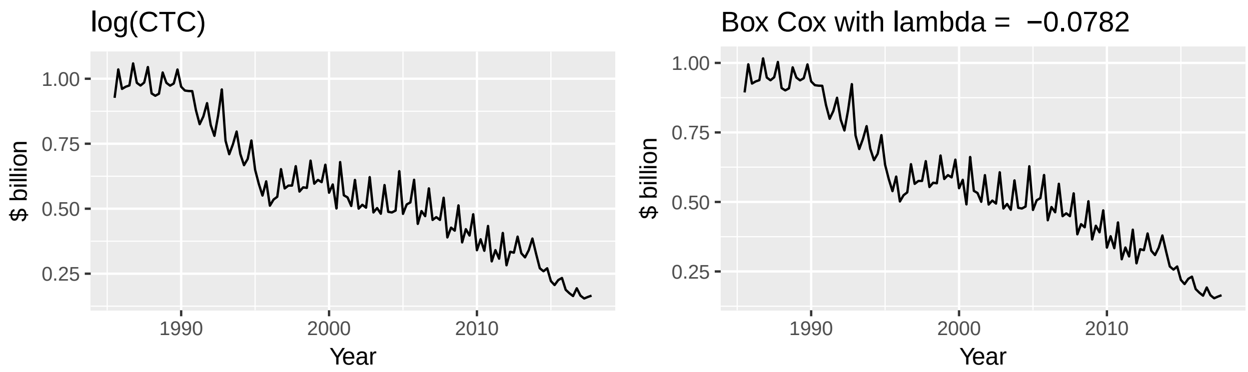

Figure 3:

2 marks

(c) Figure 4 shows the forecasts generated from the `stlf()` function with the argument `lambda=0`. Describe what this function does and how the forecasts are generated.

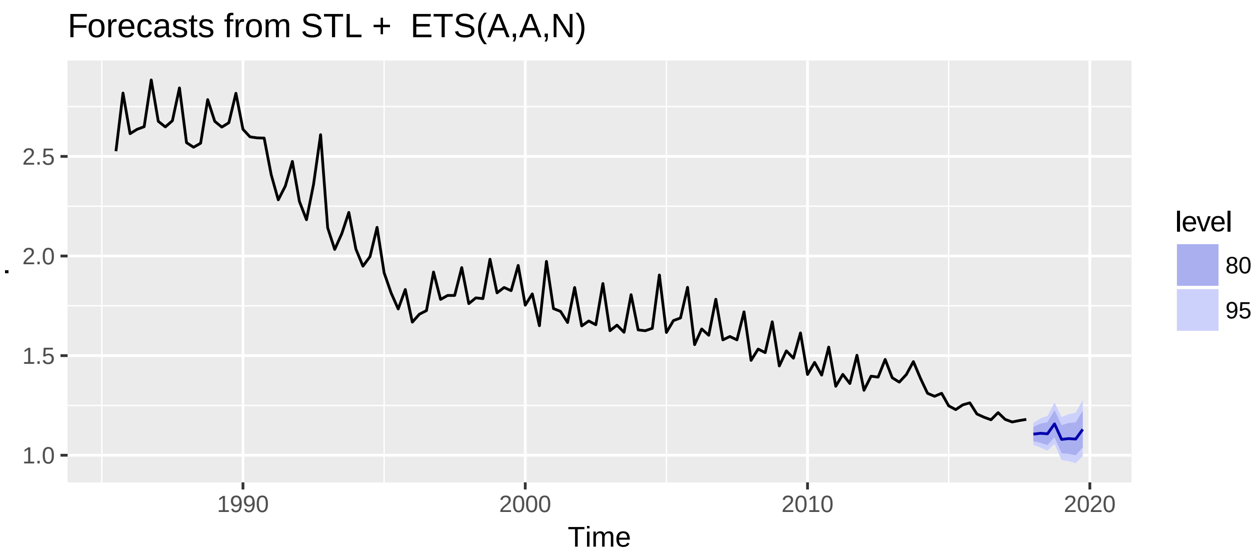

Figure 4:

4 marks

(d) You are asked to provide forecasts for the next two years for the CTC series shown in Figure 1. Consider applying each of the methods and models below. Comment, in a few words each, on whether each one is appropriate for forecasting the data. No marks will be given for simply guessing whether a method or a model is appropriate without justifying your choice.

A. Seasonal naïve method.
B. Drift method plus seasonal dummies.
C. Holt's trend method.
D. Holt-Winters multiplicative damped trend method.
E. ETS(A,A,M).
F. ETS(M,A_d,M).
G. ARIMA(0,1,4).
H. ARIMA(3,1,2)$(1,1,0)_4$.
I. ARIMA(0,0,1)$(2,0,0)_4$.
J. Regression model with time and Fourier terms.

10 marks

Total: 20 marks

— END OF QUESTION 2 —

QUESTION 3

The following R code and output concerns two models for CTC (Cigarette and tobacco consumption) in Victoria.

```r
fit1.ets <- ets(CTC)
fit1.ets
```

```
## ETS(M,N,M)
##
## Call:
##  ets(y = CTC)
##
##   Smoothing parameters:
##     alpha = 0.709
##     gamma = 0.291
##
##   Initial states:
##     l = 2.5802
##     s=0.9818 0.9801 1.0598 0.9783
##
##   sigma:  0.0308
##
##      AIC     AICc      BIC
## -111.048 -110.130  -90.975
```

```r
fit2.ets <- ets(CTC, lambda = 0)
fit2.ets
```

```
## ETS(A,A,A)
##
## Call:
##  ets(y = CTC, lambda = 0)
##
##   Box-Cox transformation: lambda= 0
##
##   Smoothing parameters:
##     alpha = 0.5083
##     beta  = 1e-04
##     gamma = 0.4536
##
##   Initial states:
##     l = 0.9583
##     b = -0.0063
##     s=-0.0017 -0.0154 0.056 -0.039
##
##   sigma:  0.0309
##
##     AIC    AICc     BIC
## -261.45 -259.95 -235.64
```

(a) Comment on the differences between the two specifications, the models selected and the estimated parameters for each of the estimated models.

4 marks

(b) Comment on Figure 5 and how this relates to your answers above.

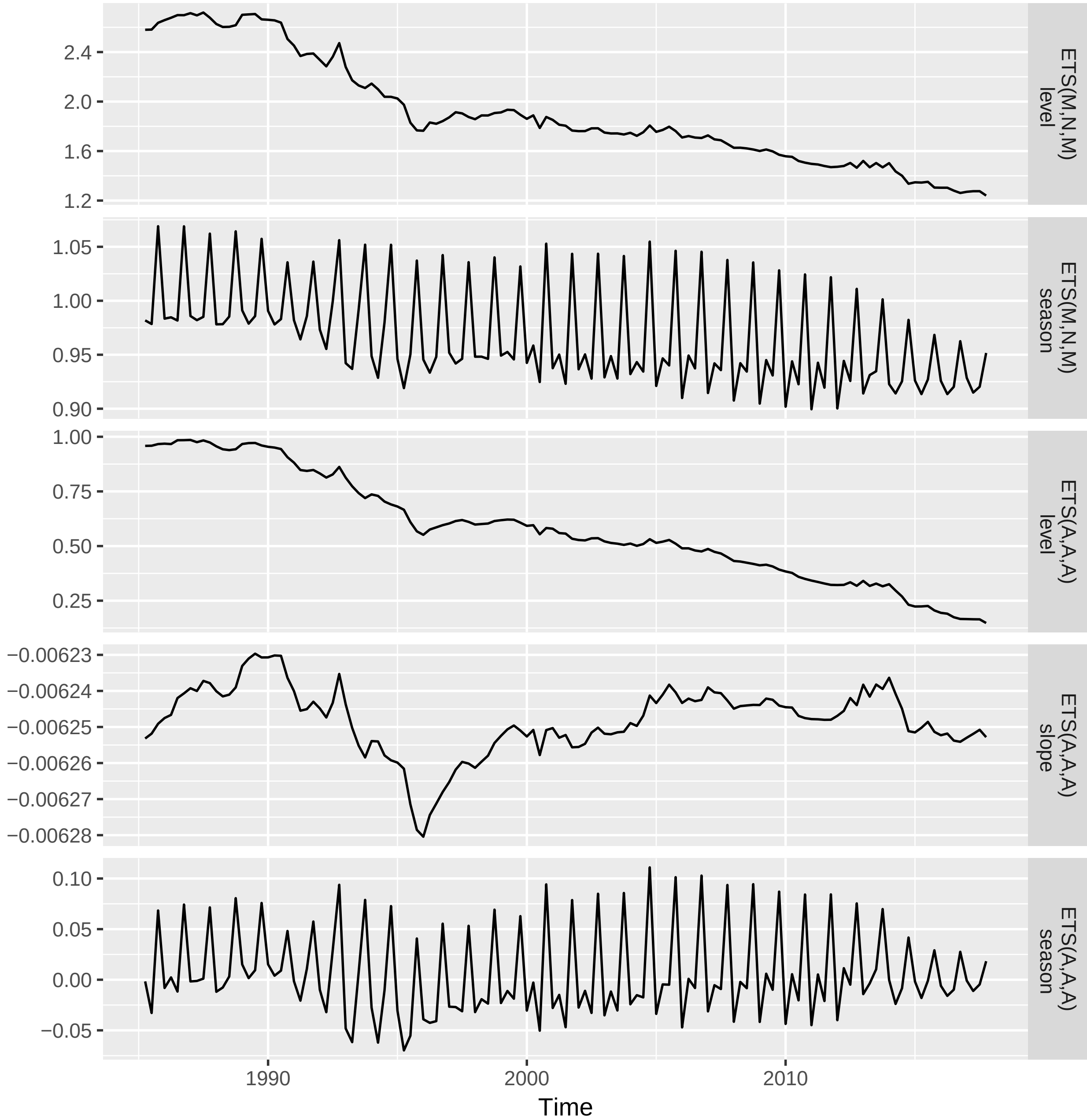

Figure 5:

4 marks

(c) Write down in full the estimated ETS model for `fit1.ets`.

3 marks

(d) The output below and Figure 6 relate to the residuals from `fit1.ets`. Comment on these in relation to the fit of the model. Give as many details as you can. What do your conclusions here imply about using the model for forecasting?

```
checkresiduals(fit1.ets)
```

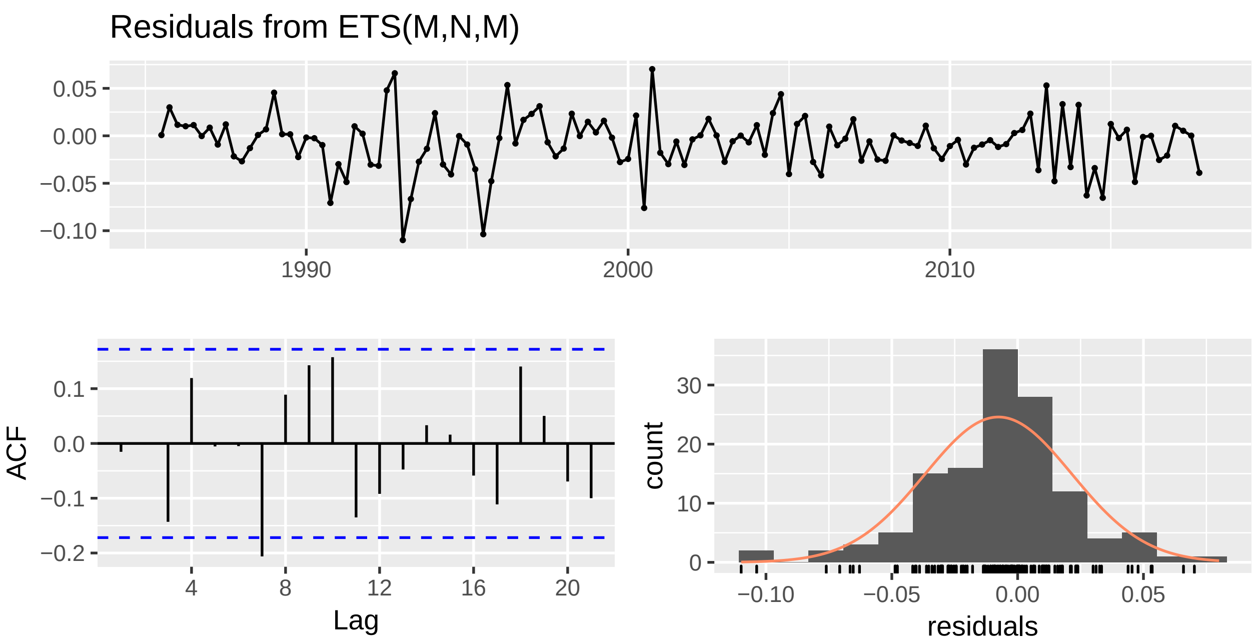

Figure 6:

```
##
##     Ljung-Box test
##
## data:  Residuals from ETS(M,N,M)
## Q* = 14.7, df = 3, p-value = 0.0021
##
## Model df: 6.   Total lags used: 9
```

4 marks

(e) Use the output below to generate 2, 4 and 8-step-ahead forecasts. In row t, `l`=ℓ_t, `s1`=s_t, . . . , `s4`=s_{t-3}.

```
fit1.ets[["states"]] %>% tail()
```

```
##               l      s1      s2      s3      s4
## 2016 Q3 1.2802 0.92029 0.91352 0.92579 0.96841
## 2016 Q4 1.2613 0.96256 0.92029 0.91352 0.92579
## 2017 Q1 1.2707 0.92862 0.96256 0.92029 0.91352
## 2017 Q2 1.2755 0.91493 0.92862 0.96256 0.92029
## 2017 Q3 1.2756 0.92033 0.91493 0.92862 0.96256
## 2017 Q4 1.2404 0.95164 0.92033 0.91493 0.92862
```

3 marks

(f) Forecasts can be generated using `fit2.ets %>% forecast(biasadj=TRUE)`. Comment on how `biasadj=TRUE` may be useful for this model.

2 marks

Total: 20 marks

— END OF QUESTION 3 —

QUESTION 4

(a) Figure 7 shows four sets of ACFs and PACFs for the CTC (cigarettes and tobacco consumption) series of Victoria plotted in Figure 1. Explain what each of these show about the stationarity, seasonality and other features of the time series.

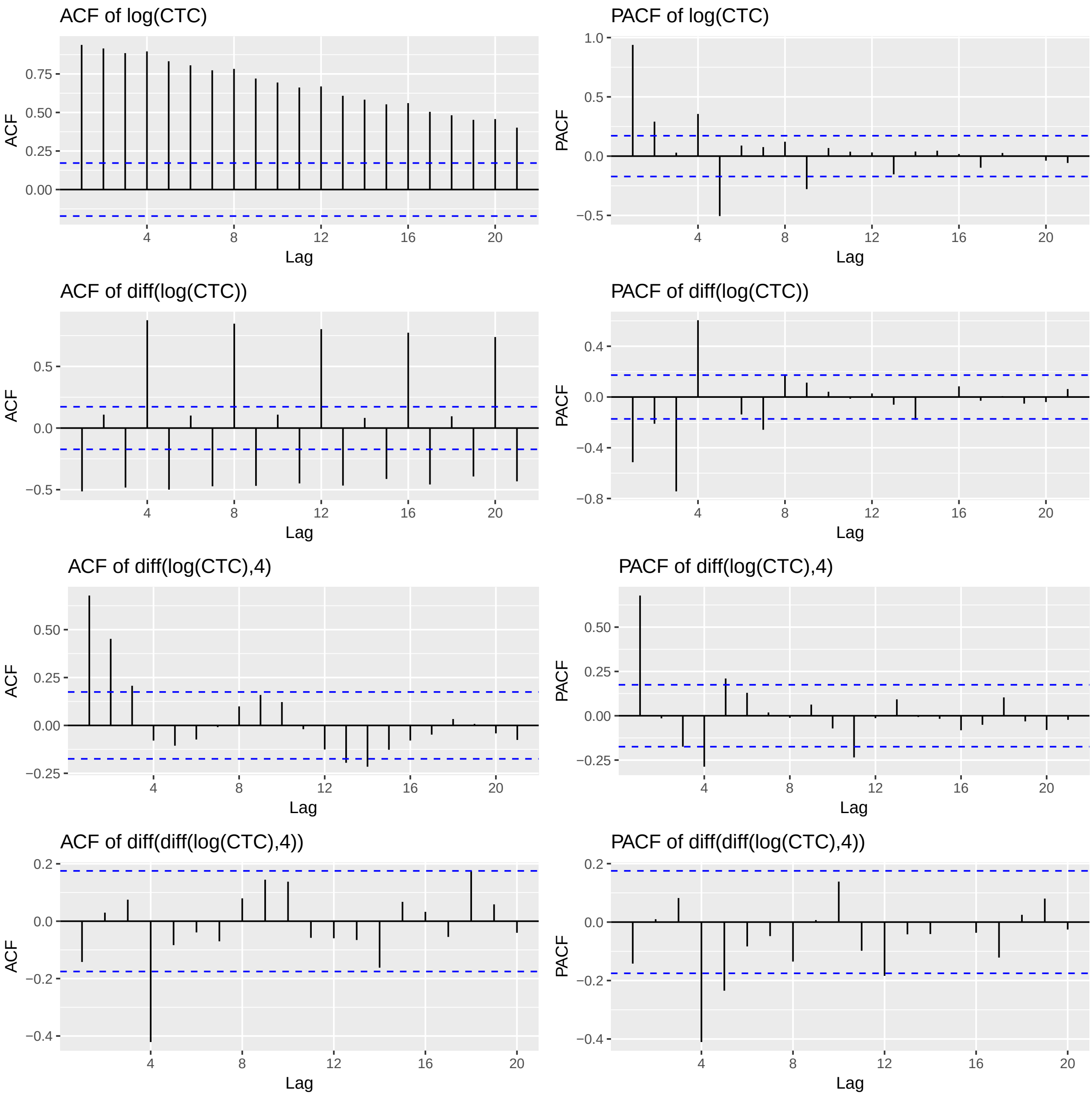

Figure 7:

4 marks

(b) Use the relevant ACFs and PACFs from Figure 7 to specify an appropriate ARIMA model with both seasonal and first differencing.

4 marks

(c) The following R code and output concerns a model for the CTC series. Write down the estimated model using backshift notation and expand this to the point where it can be used to generate point forecasts.

```r
auto.arima(CTC, lambda = 0)
```

```
## Series: CTC
## ARIMA(1,0,0)(1,1,0)[4] with drift
## Box Cox transformation: lambda= 0
##
## Coefficients:
##         ar1     sar1    drift
##       0.766   -0.378   -0.006
## s.e.  0.060    0.084    0.002
##
## sigma^2 estimated as 0.000912:  log likelihood=263.13
## AIC=-518.26   AICc=-517.93   BIC=-506.91
```

4 marks

(d) The last few values of the series are

```
##       Qtr1  Qtr2  Qtr3  Qtr4
## 2015 1.248 1.229 1.253 1.263
## 2016 1.207 1.191 1.178 1.214
## 2017 1.180 1.167 1.174 1.180
```

Use the above model to calculate a forecast and a 95% prediction interval for 2018 Q1.

5 marks

(e) The autoregressive coefficient of an AR(1) model $y_t = \phi y_{t-1} + \varepsilon_T$ where $\varepsilon_t \sim N(0, \sigma^2)$ needs to be between -1 and 1 for the process to be stationary. Is this statement true or false. Justify your answer.

3 marks

Total: 20 marks

— END OF QUESTION 4 —

QUESTION 5

In the following code, a series of dynamic regression models are fitted to the CTC data.

```r
tt <- time(CTC)
t.break1 <- 1990
t.break2 <- 1996
t.break3 <- 2000
t1 <- pmax(0,tt-t.break1)
t2 <- pmax(0,tt-t.break2)
t3 <- pmax(0,tt-t.break3)

X123 <- cbind(tt,t1,t2,t3)
X23 <- cbind(tt,t2,t3)
X13 <- cbind(tt,t1,t3)
X12 <- cbind(tt,t1,t2)
X1 <- cbind(tt,t1)
X2 <- cbind(tt,t2)
X3 <- cbind(tt,t3)
X <-  cbind(tt)

fit123 <- auto.arima(CTC, xreg=X123, lambda=0)
fit23 <- auto.arima(CTC, xreg=X23, lambda=0)
fit13 <- auto.arima(CTC, xreg=X13, lambda=0)
fit12 <- auto.arima(CTC, xreg=X12, lambda=0)
fit1 <- auto.arima(CTC, xreg=X1, lambda=0)
fit2 <- auto.arima(CTC, xreg=X2, lambda=0)
fit3 <- auto.arima(CTC, xreg=X3, lambda=0)
fit <- auto.arima(CTC, xreg=X, lambda=0)

c(AIC(fit123),AIC(fit23),AIC(fit13),AIC(fit12),
  AIC(fit1),AIC(fit2),AIC(fit3),AIC(fit))
```

```
## [1] -551.66 -531.59 -532.36 -544.69 -533.20 -530.12 -528.20 -530.20
```

```
## Series: CTC
## Regression with ARIMA(1,0,0)(1,0,1)[4] errors
## Box Cox transformation: lambda= 0
##
## Coefficients:
##          ar1    sar1     sma1     tt       t1      t2       t3
##       0.5466  0.9546  -0.4459  5e-04  -0.0701  0.0806  -0.0364
## s.e.  0.0742  0.0230   0.0904  1e-04   0.0076  0.0133   0.0112
##
## sigma^2 estimated as 0.0007467:  log likelihood=283.83
## AIC=-551.66   AICc=-550.47   BIC=-528.72
```

(a) Explain the process used in this code to select the final model, and write down the equations for the model.

6 marks

(b) How could this approach be generalized to choose the number and position of knots automatically? What problems do you imagine could happen when using such an algorithm?

6 marks

(c) When producing forecasts using this model, what assumptions are you making about the piecewise linear trend? How does this compare with fitting a similar ETS model?

4 marks

(d) Why is it better to use a seasonal ARIMA model here rather than Fourier terms to handle the seasonality in the data?

2 marks

(e) Forecasts from the model are shown in Figure 8. Do you think they look reasonable? Explain.

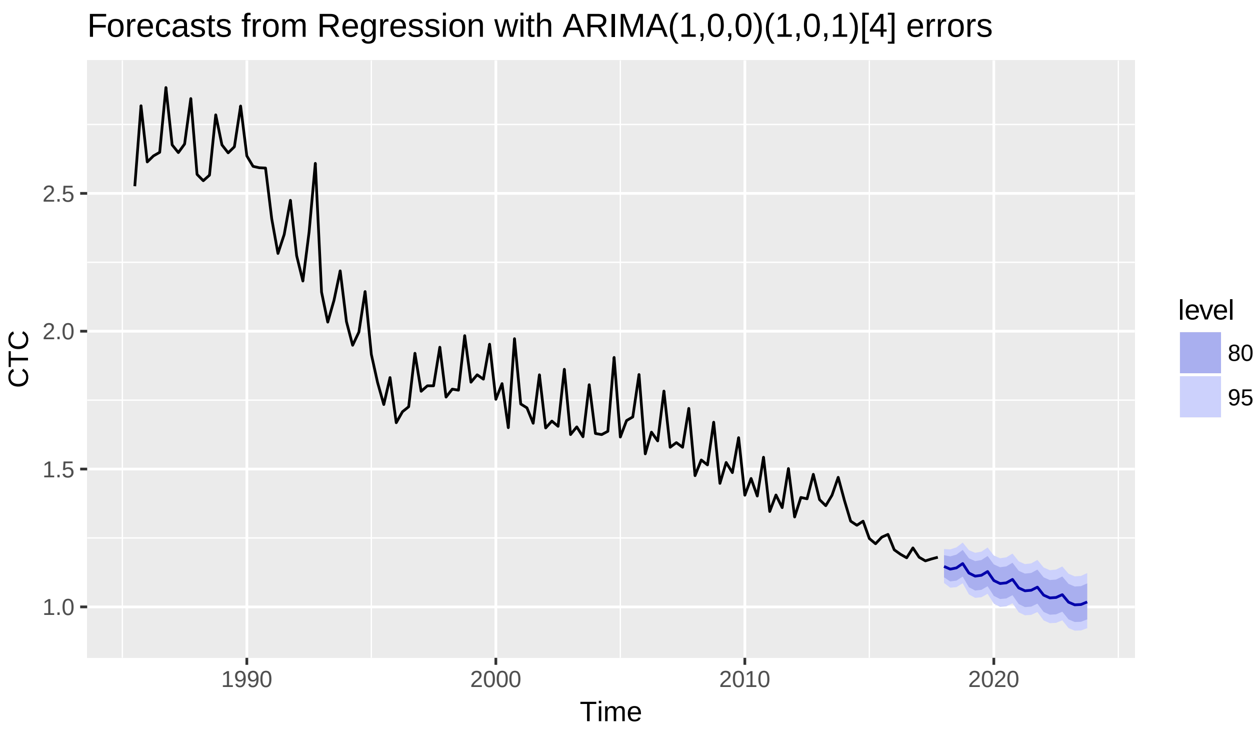

Figure 8:

2 marks

Total: 20 marks

— END OF QUESTION 5 —

Table 1: *State space equations for each of the models in the ETS framework.*

ADDITIVE ERROR MODELS

Trend	**Seasonal** N	**Seasonal** A	**Seasonal** M
N	$y_t = \ell_{t-1} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t$	$y_t = \ell_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$y_t = \ell_{t-1}s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \alpha\varepsilon_t/s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t/\ell_{t-1}$
A	$y_t = \ell_{t-1} + b_{t-1} + \varepsilon_t$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$	$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t$ $b_t = b_{t-1} + \beta\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$y_t = (\ell_{t-1} + b_{t-1})s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha\varepsilon_t/s_{t-m}$ $b_t = b_{t-1} + \beta\varepsilon_t/s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t/(\ell_{t-1} + b_{t-1})$
$\mathbf{A_d}$	$y_t = \ell_{t-1} + \phi b_{t-1} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$	$y_t = \ell_{t-1} + \phi b_{t-1} + s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t$ $b_t = \phi b_{t-1} + \beta\varepsilon_t$ $s_t = s_{t-m} + \gamma\varepsilon_t$	$y_t = (\ell_{t-1} + \phi b_{t-1})s_{t-m} + \varepsilon_t$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha\varepsilon_t/s_{t-m}$ $b_t = \phi b_{t-1} + \beta\varepsilon_t/s_{t-m}$ $s_t = s_{t-m} + \gamma\varepsilon_t/(\ell_{t-1} + \phi b_{t-1})$

MULTIPLICATIVE ERROR MODELS

Trend	**Seasonal** N	**Seasonal** A	**Seasonal** M
N	$y_t = \ell_{t-1}(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1}(1 + \alpha\varepsilon_t)$	$y_t = (\ell_{t-1} + s_{t-m})(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1} + \alpha(\ell_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + s_{t-m})\varepsilon_t$	$y_t = \ell_{t-1}s_{t-m}(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1}(1 + \alpha\varepsilon_t)$ $s_t = s_{t-m}(1 + \gamma\varepsilon_t)$
A	$y_t = (\ell_{t-1} + b_{t-1})(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t$	$y_t = (\ell_{t-1} + b_{t-1} + s_{t-m})(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1} + b_{t-1} + \alpha(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + b_{t-1} + s_{t-m})\varepsilon_t$	$y_t = (\ell_{t-1} + b_{t-1})s_{t-m}(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t$ $s_t = s_{t-m}(1 + \gamma\varepsilon_t)$
$\mathbf{A_d}$	$y_t = (\ell_{t-1} + \phi b_{t-1})(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + \phi b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1})\varepsilon_t$	$y_t = (\ell_{t-1} + \phi b_{t-1} + s_{t-m})(1 + \varepsilon_t)$ $\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$ $s_t = s_{t-m} + \gamma(\ell_{t-1} + \phi b_{t-1} + s_{t-m})\varepsilon_t$	$y_t = (\ell_{t-1} + \phi b_{t-1})s_{t-m}(1 + \varepsilon_t)$ $\ell_t = (\ell_{t-1} + \phi b_{t-1})(1 + \alpha\varepsilon_t)$ $b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1})\varepsilon_t$ $s_t = s_{t-m}(1 + \gamma\varepsilon_t)$