

# **ETC3550**

## **Applied forecasting for business and economics**

Ch12. Some practical forecasting  
issues

[OTexts.org/fnp3/](https://OTexts.org/fnp3/)



# Outline

- 1 Models for different frequencies
- 2 Ensuring forecasts stay within limits
- 3 Forecast combinations
- 4 Missing values
- 5 Outliers

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# Models for different frequencies

## Models for annual data

- ETS, ARIMA, Dynamic regression

# Models for different frequencies

## Models for annual data

- ETS, ARIMA, Dynamic regression

## Models for quarterly data

- ETS, ARIMA/SARIMA, Dynamic regression, Dynamic harmonic regression, STL+ETS, STL+ARIMA

# Models for different frequencies

## Models for annual data

- ETS, ARIMA, Dynamic regression

## Models for quarterly data

- ETS, ARIMA/SARIMA, Dynamic regression, Dynamic harmonic regression, STL+ETS, STL+ARIMA

## Models for monthly data

- ETS, ARIMA/SARIMA, Dynamic regression, Dynamic harmonic regression, STL+ETS, STL+ARIMA

# Models for different frequencies

## Models for weekly data

- ARIMA/SARIMA, Dynamic regression, Dynamic harmonic regression, STL+ETS, STL+ARIMA, TBATS

# Models for different frequencies

## Models for weekly data

- ARIMA/SARIMA, Dynamic regression, Dynamic harmonic regression, STL+ETS, STL+ARIMA, TBATS

## Models for daily, hourly and other sub-daily data

- ARIMA/SARIMA, Dynamic regression, Dynamic harmonic regression, STL+ETS, STL+ARIMA, TBATS

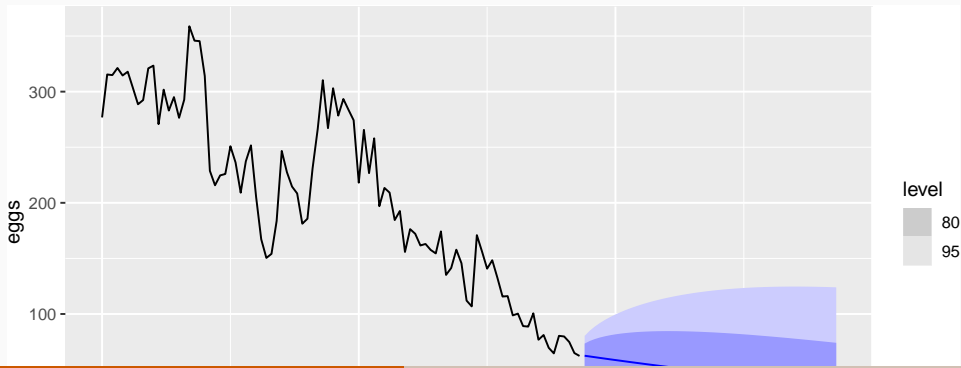


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# Positive forecasts

```
recent_prices <- prices |> filter(!is.na(eggs))
recent_prices |>
  model(ETS(log(eggs) ~ error("A") + trend("A") + season("N")))|>
  forecast(h = 50) |>
  autoplot(recent_prices)
```



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# Forecast combinations

## Clemen (1989)

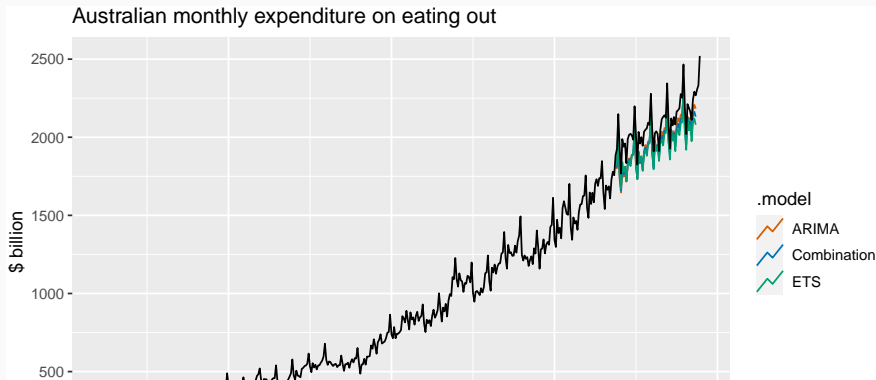
“The results have been virtually unanimous: combining multiple forecasts leads to increased forecast accuracy. ... In many cases one can make dramatic performance improvements by simply averaging the forecasts.”

# Forecast combinations

```
aus_cafe <- aus_retail |>
  filter(Industry == "Cafes, restaurants and catering services") |>
  summarise(Turnover = sum(Turnover))
fc <- aus_cafe |>
  filter(Month <= yearmonth("2013 Sep")) |>
  model(
    ETS = ETS(Turnover),
    ARIMA = ARIMA(Turnover)
  ) |>
  mutate(
    Combination = (ETS + ARIMA) / 2
  ) |>
  forecast(h = "5 years")
```

# Forecast combinations

```
fc |> autoplot(aus_cafe, level = NULL) +  
  labs(  
    x = "Year", y = "$ billion",  
    title = "Australian monthly expenditure on eating out"  
  )
```



# Forecast combinations

```
fc |> accuracy(aus_cafe)
```

```
## # A tibble: 3 x 10
```

##	.model	.type	ME	RMSE	MAE	MPE	MAPE	MASE	RMSSE	ACF1
##	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
## 1	ARIMA	Test	112.	122.	112.	5.44	5.44	1.80	1.50	0.510
## 2	Combination	Test	120.	125.	120.	5.81	5.81	1.93	1.55	0.382
## 3	ETS	Test	128.	133.	128.	6.18	6.18	2.06	1.64	0.324

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# Missing values

## Functions which can handle missing values

- `ARIMA()`
- `TSLM()`
- `NNETAR()`
- `VAR()`
- `FASSTER()`

## Models which cannot handle missing values

- `ETS()`
- `STL()`
- `TBATS()`

# Missing values

## Functions which can handle missing values

- `ARIMA()`
- `TSLM()`
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- `FASSTER()`

## Models which cannot handle missing values

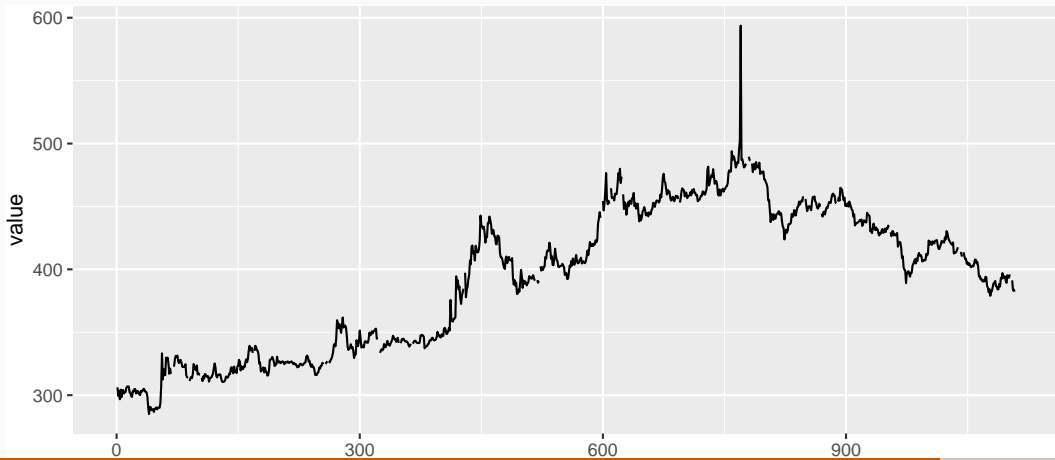
- `ETS()`
- `STL()`
- `TBATS()`

## What to do?

- 1 Model section of data after last missing value.

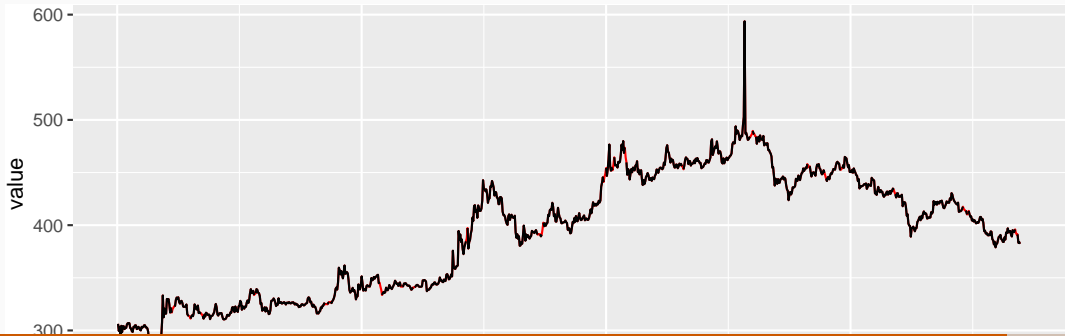
# Missing values

```
gold <- as_tsibble(forecast::gold)
gold |> autoplot(value)
```



# Missing values

```
gold_complete <- gold |>  
  model(ARIMA(value)) |>  
  interpolate(gold)  
gold_complete |>  
  autoplot(value, colour = "red") +  
  autolayer(gold, value)
```



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# Outliers

```
fit <- gold |>
  model(ARIMA(value))
augment(fit) |>
  mutate(stdres = .resid / sd(.resid, na.rm = TRUE)) |>
  filter(abs(stdres) > 10)
```

```
## # A tsibble: 2 x 7 [1]
```

```
## # Key:           .model [1]
```

##	.model	index	value	.fitted	.resid	.innov	stdres
##	<chr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
## 1	ARIMA(value)	770	594.	499.	94.7	94.7	16.4
## 2	ARIMA(value)	771	487.	562.	-74.8	-74.8	-12.9