

# ETC3550/ETC5550

## Applied forecasting

Week 6: Non-seasonal exponential smoothing



# Historical perspective

- Developed in the 1950s and 1960s as methods (algorithms) to produce point forecasts.
- Combine a “level”, “trend” (slope) and “seasonal” component to describe a time series.
- The rate of change of the components are controlled by “smoothing parameters”:  $\alpha$ ,  $\beta$  and  $\gamma$  respectively.
- Need to choose best values for the smoothing parameters (and initial states).
- Equivalent ETS state space models developed in the 1990s and 2000s.
- ETS and the PBS

**Exponential Smoothing**  
**Error Trend Seasonal**

## Exponential Smoothing Error Trend Seasonal

**Error:** Additive, Multiplicative

**Trend:** None, Additive, Additive damped

**Seasonal:** None, Additive, Multiplicative

## Exponential Smoothing Error Trend Seasonal

**Error:** Additive, Multiplicative

**Trend:** None, Additive, Additive damped

**Seasonal:** None, Additive, Multiplicative

- ETS(A,N,N): **A**dditive Error, **N**o Trend, **N**o Seasonality

## Exponential Smoothing Error Trend Seasonal

**Error:** Additive, Multiplicative

**Trend:** None, Additive, Additive damped

**Seasonal:** None, Additive, Multiplicative

- ETS(A,N,N): **A**dditive Error, **N**o Trend, **N**o Seasonality
- ETS(M,A,N): **M**ultiplicative Error, **A**dditive Trend, **N**o Seasonality

## Exponential Smoothing Error Trend Seasonal

**Error:** Additive, Multiplicative

**Trend:** None, Additive, Additive damped

**Seasonal:** None, Additive, Multiplicative

- ETS(A,N,N): **A**dditive Error, **N**o Trend, **N**o Seasonality
- ETS(M,A,N): **M**ultiplicative Error, **A**dditive Trend, **N**o Seasonality
- ETS(M,A,M): **M**ultiplicative Error, **A**dditive Trend, **M**ultiplicative Seasonality

etc

# ETS(A,N,N): SES with additive errors

State equation

$$l_t = l_{t-1} + \alpha \varepsilon_t$$

Observation equation

$$y_t = l_{t-1} + \varepsilon_t$$

Forecast equation

$$\hat{y}_{t+h|t} = l_t$$



# ETS(A,N,N): SES with additive errors

State equation

$$l_t = l_{t-1} + \alpha \varepsilon_t$$

Observation equation

$$y_t = l_{t-1} + \varepsilon_t$$

Forecast equation

$$\hat{y}_{t+h|t} = l_t$$

- Forecast errors:  $\varepsilon_t = y_t - \hat{y}_{t|t-1} \sim \text{NID}(0, \sigma^2)$
- “innovations” or “single source of error” because equations have the same error process,  $\varepsilon_t$ .

# ETS(A,N,N): SES with additive errors

Note that  $\varepsilon_t = y_t - \ell_{t-1}$ . So

$$\begin{aligned}\hat{y}_{t+1|t} &= \ell_t = \ell_{t-1} + \alpha \varepsilon_t \\ &= \ell_{t-1} + \alpha(y_t - \ell_{t-1}) \\ &= \alpha y_t + (1 - \alpha)\ell_{t-1} \\ &= \alpha y_t + (1 - \alpha)[\alpha y_{t-1} + (1 - \alpha)\ell_{t-2}] \\ &= \alpha y_t + \alpha(1 - \alpha)y_{t-1} + (1 - \alpha)^2 \ell_{t-2} \\ &\dots \\ &= \alpha \sum_{j=0}^{t-1} (1 - \alpha)^j y_{t-j} + (1 - \alpha)^t \ell_0\end{aligned}$$

# ETS(A,N,N): SES with additive errors

Note that  $\ell_t = \ell_{t-1} + \alpha \varepsilon_t$ . So

$$\begin{aligned}y_{T+h} &= \ell_{T+h-1} + \varepsilon_{T+h} \\&= \ell_{T+h-2} + \alpha \varepsilon_{T+h-1} + \varepsilon_{T+h} \\&= \ell_{T+h-3} + \alpha \varepsilon_{T+h-2} + \alpha \varepsilon_{T+h-1} + \varepsilon_{T+h} \\&\dots \\&= \ell_T + \alpha \sum_{j=1}^{h-1} \varepsilon_{T+h-j} + \varepsilon_{T+h}.\end{aligned}$$

Therefore  $E(y_{T+h} | y_1, \dots, y_T) = \ell_T$

# ETS(A,N,N): SES with additive errors

Note that  $\ell_t = \ell_{t-1} + \alpha \varepsilon_t$ . So

$$\begin{aligned}y_{T+h} &= \ell_{T+h-1} + \varepsilon_{T+h} \\&= \ell_{T+h-2} + \alpha \varepsilon_{T+h-1} + \varepsilon_{T+h} \\&= \ell_{T+h-3} + \alpha \varepsilon_{T+h-2} + \alpha \varepsilon_{T+h-1} + \varepsilon_{T+h} \\&\dots \\&= \ell_T + \alpha \sum_{j=1}^{h-1} \varepsilon_{T+h-j} + \varepsilon_{T+h}.\end{aligned}$$

Therefore  $\text{Var}(y_{T+h} | y_1, \dots, y_T) = \alpha^2 \sum_{j=1}^{h-1} \sigma^2 + \sigma^2 = \sigma^2 [1 + \alpha^2(h-1)]$ .

# ETS(A,A,N): Holt's method with additive errors

State equations

$$\ell_t = \ell_{t-1} + b_{t-1} + \alpha \varepsilon_t$$

$$b_t = b_{t-1} + \beta \varepsilon_t$$

Observation equation

$$y_t = \ell_{t-1} + b_{t-1} + \varepsilon_t$$

Forecast equation

$$\hat{y}_{t+h|t} = \ell_t + hb_t$$

- Forecast errors:  $\varepsilon_t = y_t - \hat{y}_{t|t-1} \sim \text{NID}(0, \sigma^2)$

## ETS(M,N,N): SES with multiplicative errors.

State equation	$\ell_t = \ell_{t-1}(1 + \alpha\varepsilon_t)$
Observation equation	$y_t = \ell_{t-1}(1 + \varepsilon_t)$
Forecast equation	$\hat{y}_{t+h t} = \ell_t$

- Relative forecast errors:  $\varepsilon_t = \frac{y_t - \hat{y}_{t|t-1}}{\hat{y}_{t|t-1}} \sim \text{NID}(0, \sigma^2)$
- Same point forecasts as ETS(A,N,N) with additive errors and same  $\alpha$ .
- Different prediction intervals from ETS(A,N,N).

# ETS(M,A,N): Holt's method with multiplicative errors.

State equations

$$\ell_t = (\ell_{t-1} + b_{t-1})(1 + \alpha \varepsilon_t)$$

$$b_t = b_{t-1} + \beta(\ell_{t-1} + b_{t-1})\varepsilon_t$$

Observation equation

$$y_t = (\ell_{t-1} + b_{t-1})(1 + \varepsilon_t)$$

Forecast equation

$$\hat{y}_{t+h|t} = \ell_t + hb_t$$

- Relative forecast errors:  $\varepsilon_t = \frac{y_t - \hat{y}_{t|t-1}}{\hat{y}_{t|t-1}} \sim \text{NID}(0, \sigma^2)$
- Same point forecasts as ETS(A,A,N) with additive errors and same  $\alpha$  and  $\beta$
- Different prediction intervals from ETS(A,A,N).

# Summary of models so far

## **Simple exponential smoothing**

ETS(A,N,N) – additive errors

ETS(M,N,N) – multiplicative errors

## **Holt's linear trend method**

ETS(A,A,N) – additive errors, additive trend

ETS(M,A,N) – multiplicative errors, additive trend



# ETS(A,Ad,N): Damped trend with additive errors

State equations

$$\ell_t = \ell_{t-1} + \phi b_{t-1} + \alpha \varepsilon_t$$

$$b_t = \phi b_{t-1} + \beta \varepsilon_t$$

Observation equation

$$y_t = \ell_{t-1} + \phi b_{t-1} + \varepsilon_t$$

Forecast equation

$$\hat{y}_{t+h|t} = \ell_t + (\phi + \phi^2 + \dots + \phi^h) b_t$$

- Forecast errors:  $\varepsilon_t = y_t - \hat{y}_{t|t-1} \sim \text{NID}(0, \sigma^2)$
- Damping parameter  $0 < \phi < 1$ .
- If  $\phi = 1$ , identical to Holt's linear trend.
- As  $h \rightarrow \infty$ ,  $\hat{y}_{T+h|T} \rightarrow \ell_T + \phi b_T / (1 - \phi)$ .
- Short-run forecasts trended, long-run forecasts constant.

# ETS(M,Ad,N): Damped trend with multiplicative errors

State equations

$$\ell_t = (\ell_{t-1} + \phi b_{t-1})(1 + \alpha \varepsilon_t)$$

$$b_t = \phi b_{t-1} + \beta(\ell_{t-1} + \phi b_{t-1})\varepsilon_t$$

Observation equation

$$y_t = (\ell_{t-1} + \phi b_{t-1})(1 + \varepsilon_t)$$

Forecast equation

$$\hat{y}_{t+h|t} = \ell_t + (\phi + \phi^2 + \dots + \phi^h)b_t$$

- Relative forecast errors:  $\varepsilon_t = \frac{y_t - \hat{y}_{t|t-1}}{\hat{y}_{t|t-1}} \sim \text{NID}(0, \sigma^2)$
- Damping parameter  $0 < \phi < 1$ .
- If  $\phi = 1$ , identical to Holt's linear trend.
- As  $h \rightarrow \infty$ ,  $\hat{y}_{T+h|T} \rightarrow \ell_T + \phi b_T / (1 - \phi)$ .
- Short-run forecasts trended, long-run forecasts constant.

# Non-seasonal ETS models

## **Simple exponential smoothing**

ETS(A,N,N) – additive errors

ETS(M,N,N) – multiplicative errors

## **Holt's linear trend method**

ETS(A,A,N) – additive errors, additive trend

ETS(M,A,N) – multiplicative errors, additive trend

## **Damped trend method**

ETS(A,Ad,N) – additive errors, damped trend

ETS(M,Ad,N) – multiplicative errors, damped trend

# Parameters

$\alpha$  controls the flexibility of the **level**

- If  $\alpha = 0$ , the level never updates (mean)
- If  $\alpha = 1$ , the level updates completely (naive)

$\beta$  controls the flexibility of the **trend**

- If  $\beta = 0$ , the trend is linear
- If  $\beta = 1$ , the trend changes suddenly every observation

$\phi$  controls the rate of **damping**

- If  $\phi = 1$ , there is no damping (trend is linear)
- If  $0 < \phi < 1$ , the trend converges to constant

# States

$\ell_t$  = level at time  $t$

$b_t$  = slope at time  $t$