

# ETC3550/ETC5550

## Applied forecasting

Week 2: Time series graphics



# Outline

- 1 dplyr functions
- 2 Time series graphics
- 3 Seasonality and cyclicity
- 4 Scatterplots
- 5 White noise and random walks
- 6 Lag plots and ACFs

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# dplyr functions

- filter: choose rows
- select: choose columns
- mutate: make new columns
- group\_by: group rows
- summarise: summarise across groups
- reframe: summarise multiple rows across groups

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# Time series graphics

- Time plots: `autoplot()`
- Seasonal plots: `gg_season()`
- Seasonal subseries plots: `gg_subseries()`
- Lag plots: `gg_lag()`
- ACF plots: `ACF()` | `> autoplot()`

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# Time series patterns

**Trend** pattern exists when there is a long-term increase or decrease in the data.

**Seasonal** pattern exists when a series is influenced by seasonal factors (e.g., the quarter of the year, the month, or day of the week).

**Cyclic** pattern exists when data exhibit rises and falls that are *not of fixed period* (duration usually of at least 2 years).



# Time series components

## Differences between seasonal and cyclic patterns:

- seasonal pattern constant length; cyclic pattern variable length
- average length of cycle longer than length of seasonal pattern
- magnitude of cycle more variable than magnitude of seasonal pattern

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The timing of peaks and troughs is predictable with seasonal data, but unpredictable in the long term with cyclic data.

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# White noise and random walks

## White noise

$\varepsilon_t \sim$  independent and identically distributed with mean zero and constant variance.

## Random walks

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

where  $\varepsilon_t$  is a white noise variable.

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# Sampling distribution of autocorrelations

Sampling distribution of  $r_k$  for white noise data is asymptotically  $N(0, 1/T)$ .

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Sampling distribution of  $r_k$  for white noise data is asymptotically  $N(0, 1/T)$ .

- 95% of all  $r_k$  for white noise must lie within  $\pm 1.96/\sqrt{T}$ .
- If this is not the case, the series is probably not WN.
- Common to plot lines at  $\pm 1.96/\sqrt{T}$  when plotting ACF. These are the **critical values**.



# Trend and seasonality in ACF plots

- When data have a trend, the autocorrelations for small lags tend to be large and positive.
- When data are seasonal, the autocorrelations will be larger at the seasonal lags (i.e., at multiples of the seasonal frequency)
- When data are trended and seasonal, you see a combination of these effects.