FPP3 Chapter 2 Graphics Exercise

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Contents

1 Explore four time series

Series explored:

- **Bricks** from `aus_production`
- **Lynx** from `pelt`
- **Close** from `gafa_stock`
- **Demand** from `vic_elec`

1.1 Dataset help pages

```
?aus_production
?pelt
?gafa_stock
?vic_elec
```

1.2 Time interval of each series

Below, I compute the interval from each tsibble index.

```
bricks_ts <- aus_production |> select(Quarter, Bricks)
lynx_ts <- pelt_long(pelt) |> filter(Animal == "Lynx")
close_ts  <- gafa_stock |> select(Symbol, Date, Close)
demand_ts <- vic_elec |> select(Time, Demand)

bricks_interval <- bricks_ts |> tsibble::interval()
lynx_interval   <- lynx_ts   |> tsibble::interval()
close_interval  <- close_ts  |> tsibble::interval()
demand_interval <- demand_ts |> tsibble::interval()

bricks_interval
```

```
## <interval[1]>
## [1] 1Q
```

```
lynx_interval
```

```
## <interval[1]>
## [1] 1Y
```

```
close_interval
```

```
## <interval[1]>
## [1] !
```

```
demand_interval
```

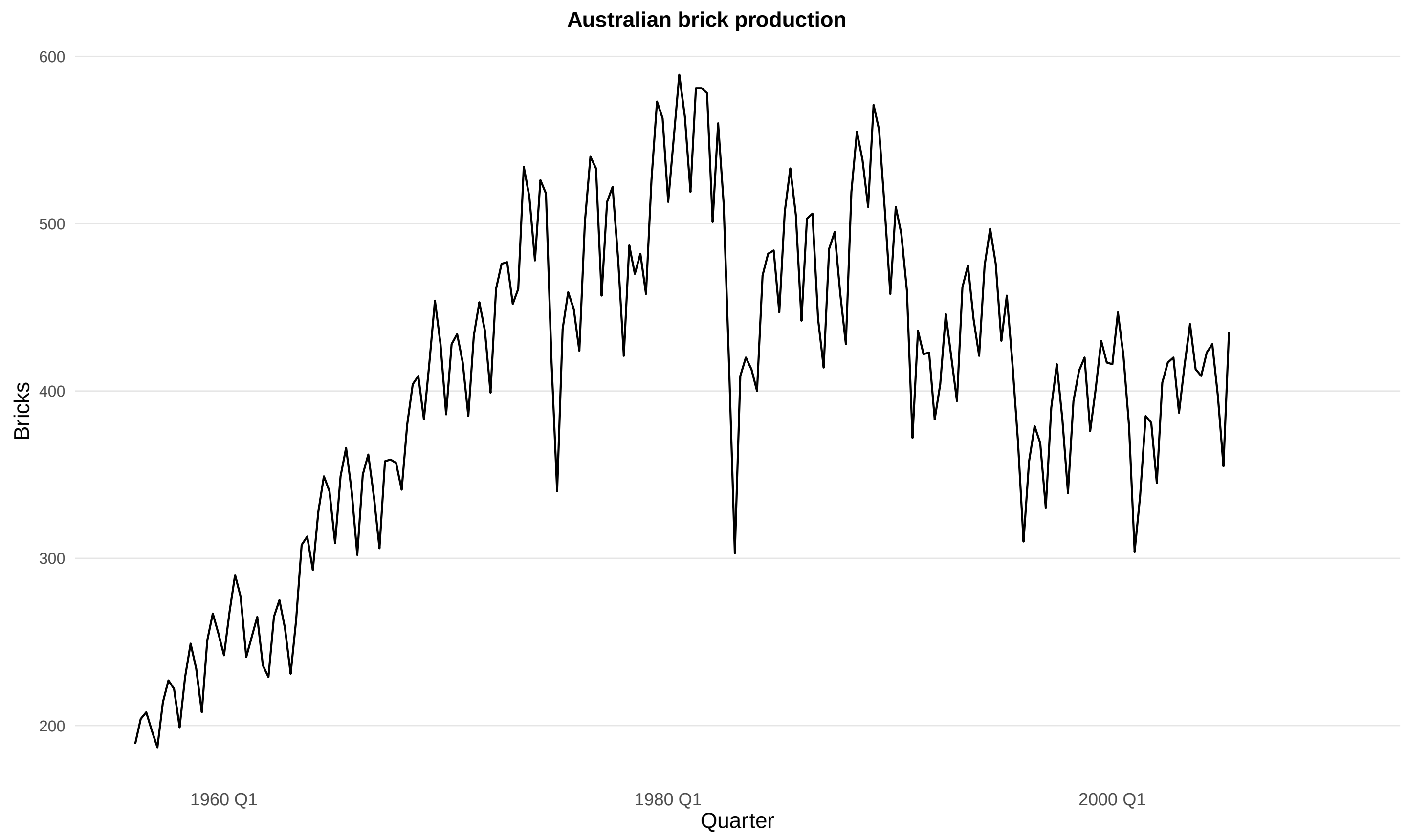
```
## <interval[1]>
## [1] 30m
```

Answer (interpretation):

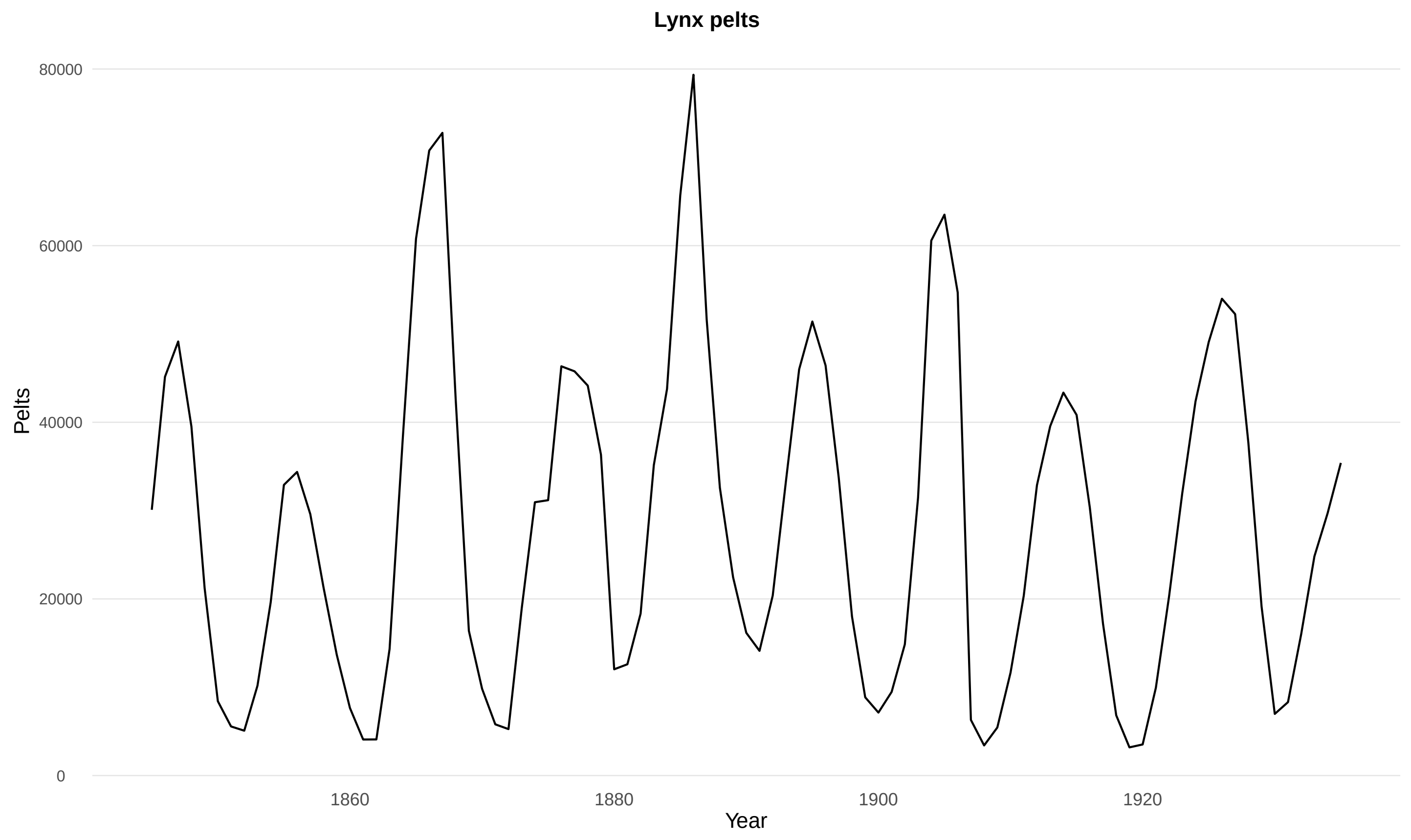
- `aus_production` (**Bricks**) is **quarterly** (index is `yearquarter`).
- `pelt` (**Lynx**) is **annual** (index is `year`).
- `gafa_stock` (**Close**) is **daily trading days** (dates exist only on trading days, so the calendar is not strictly regular daily).
- `vic_elec` (**Demand**) is **half-hourly** (sub-daily regular interval).

1.3 Time plots (autoplot)

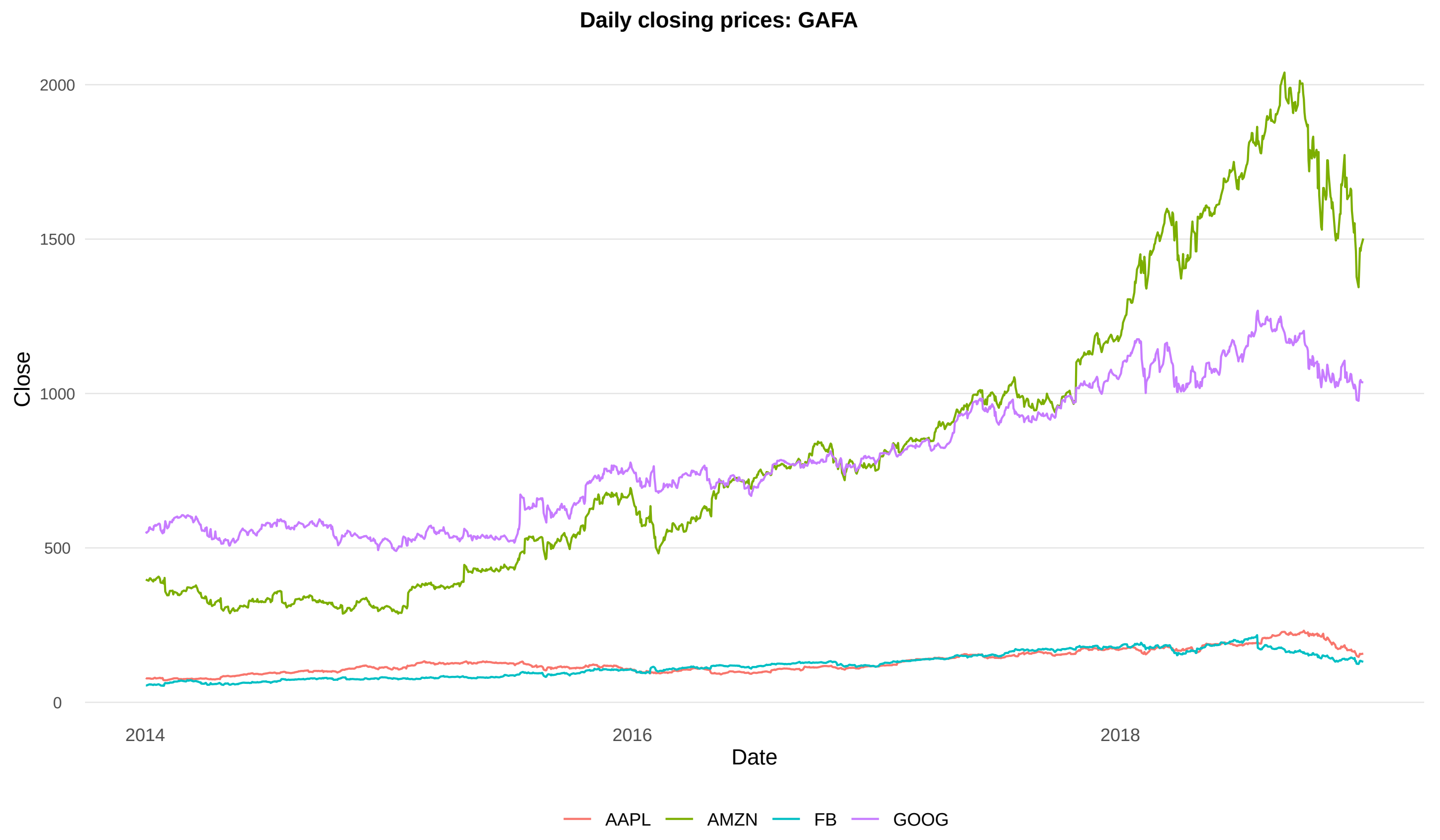
```
# Bricks
bricks_ts |>
  autoplot(Bricks) +
  labs(title = "Australian brick production", x = "Quarter", y = "Bricks")
```



```
# Lynx
lynx_ts |>
  autoplot(value) +
  labs(title = "Lynx pelts", x = "Year", y = "Pelts")
```

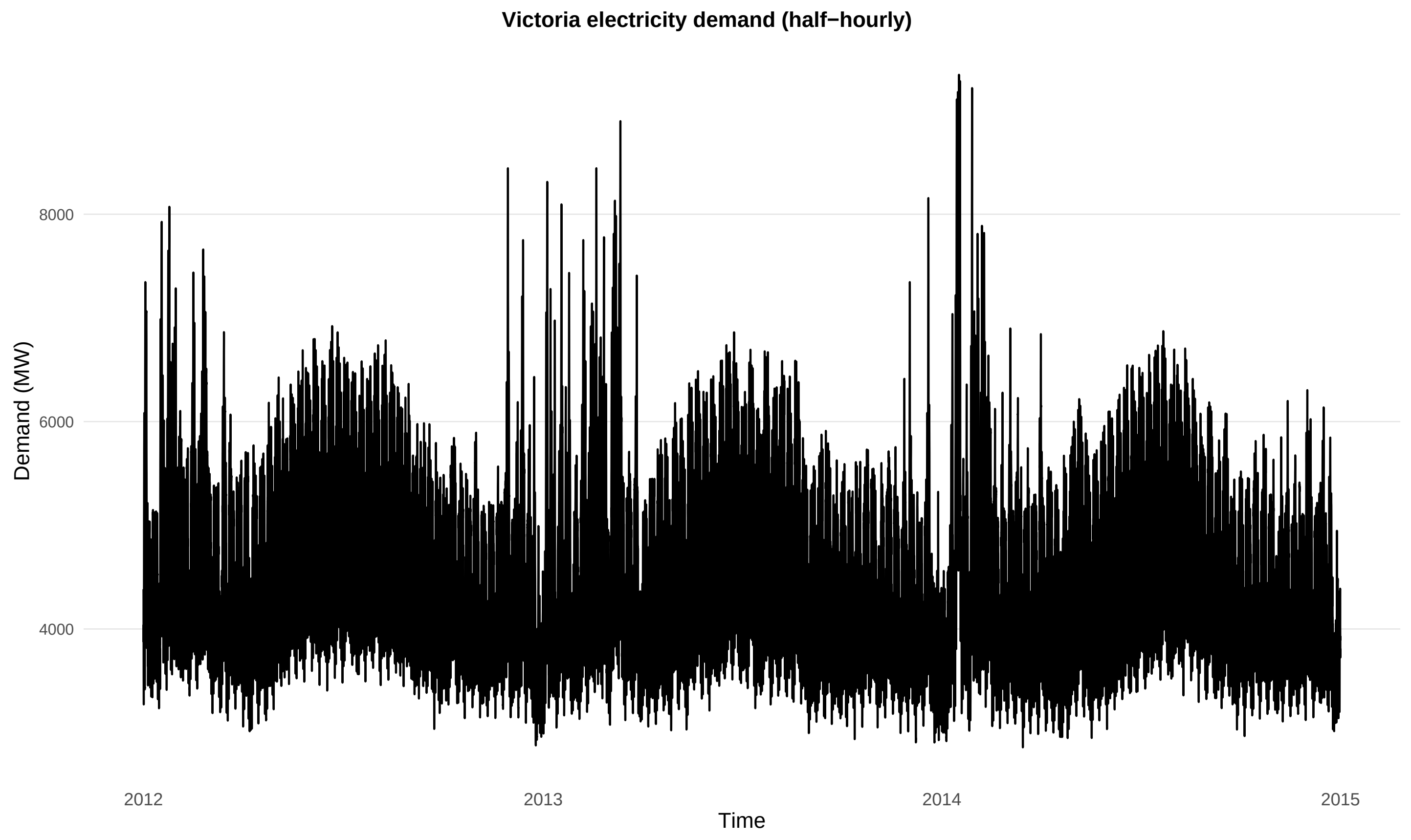


```r
# Close (all four stocks)
gafa_stock |>
  autoplot(Close) +
  labs(title = "Daily closing prices: GAFA", x = "Date", y = "Close")
```



1.4 Demand plot with modified axis labels and title

```r
demand_ts |>
  autoplot(Demand) +
  labs(
    title = "Victoria electricity demand (half-hourly)",
    x = "Time",
    y = "Demand (MW)"
  )
```



2 Peak closing price day(s) for each GAFA stock

Find the trading day(s) (ties possible) corresponding to the maximum closing price for each of the four stocks.

```
gafa_peaks <- gafa_stock |>
  group_by(Symbol) |>
  filter(Close == max(Close, na.rm = TRUE)) |>
  arrange(Symbol, Date) |>
  select(Symbol, Date, Close)

gafa_peaks
```

```
## # A tsibble: 4 x 3 [!]
## # Key:       Symbol [4]
## # Groups:    Symbol [4]
##   Symbol Date       Close
##   <chr>  <date>     <dbl>
## 1 AAPL   2018-10-03  232.
## 2 AMZN   2018-09-04 2040.
## 3 FB     2018-07-25  218.
## 4 GOOG   2018-07-26 1268.
```

Answer: The table above lists the peak closing date(s) and peak `Close` for each symbol.

3 tute1.csv: import, tsibble conversion, plots, and faceting

tute1.csv contains quarterly series **Sales**, **AdBudget**, and **GDP** (inflation-adjusted).

3.1 Download and read the data

```
tute1_url <- "https://otexts.com/fpp3/extrafiles/tute1.csv"
tute1 <- readr::read_csv(tute1_url)

dplyr::glimpse(tute1)
```

```
## Rows: 100
## Columns: 4
## $ Quarter  <date> 1981-03-01, 1981-06-01, 1981-09-01, 1981-12-01, 1982-03-01, ~
## $ Sales    <dbl> 1020.2, 889.2, 795.0, 1003.9, 1057.7, 944.4, 778.5, 932.5, 99~
## $ AdBudget <dbl> 659.2, 589.0, 512.5, 614.1, 647.2, 602.0, 530.7, 608.4, 637.9~
## $ GDP      <dbl> 251.8, 290.9, 290.8, 292.4, 279.1, 254.0, 295.6, 271.7, 259.6~
```

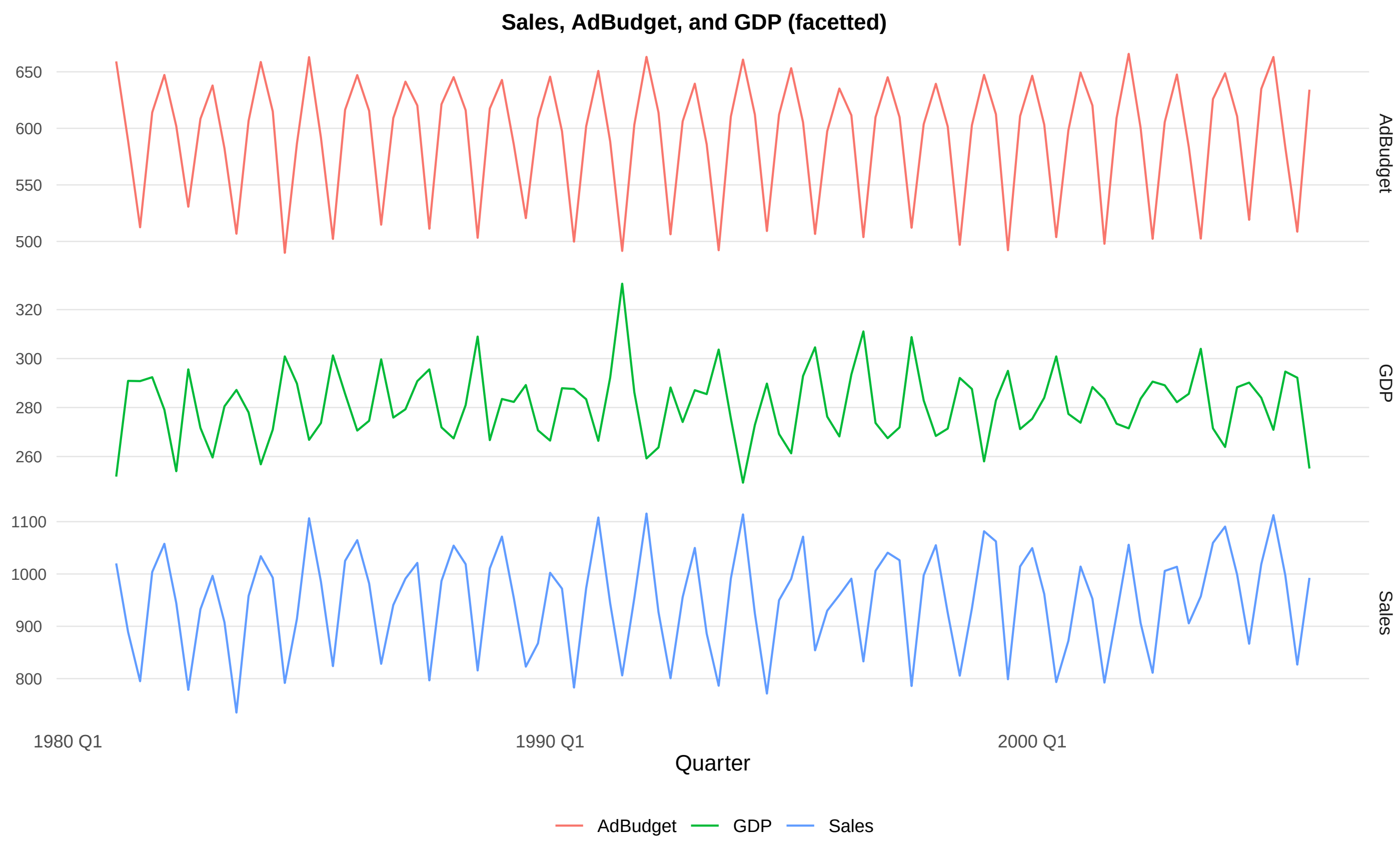
3.2 Convert to a quarterly tsibble

```
mytimeseries <- tute1 |>
  mutate(Quarter = yearquarter(Quarter)) |>
  as_tsibble(index = Quarter)

mytimeseries
```

```
## # A tsibble: 100 x 4 [1Q]
##    Quarter Sales AdBudget   GDP
##      <qtr> <dbl>    <dbl> <dbl>
##  1 1981 Q1 1020.     659.  252.
##  2 1981 Q2  889.     589   291.
##  3 1981 Q3  795      512.  291.
##  4 1981 Q4 1004.     614.  292.
##  5 1982 Q1 1058.     647.  279.
##  6 1982 Q2  944.     602   254
##  7 1982 Q3  778.     531.  296.
##  8 1982 Q4  932.     608.  272.
##  9 1983 Q1  996.     638.  260.
## 10 1983 Q2  908.     582.  280.
## # i 90 more rows
```

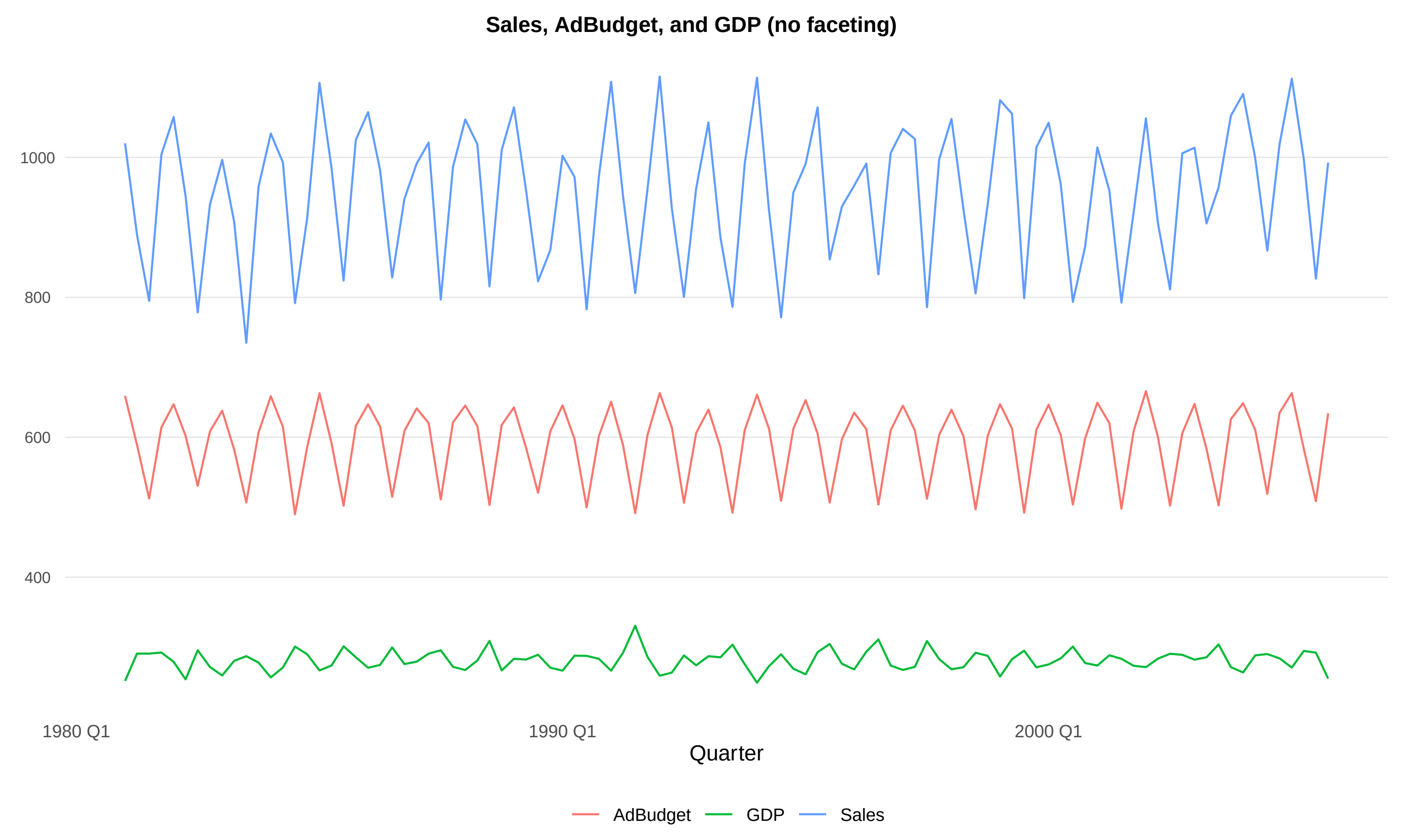
3.3 Plot all three series with facets

```r
mytimeseries |>
  pivot_longer(-Quarter) |>
  ggplot(aes(x = Quarter, y = value, colour = name)) +
  geom_line() +
  facet_grid(name ~ ., scales = "free_y") +
  labs(title = "Sales, AdBudget, and GDP (facetted)", x = "Quarter", y = "")
```



3.4 Plot without `facet_grid()`

```r
mytimeseries |>
  pivot_longer(-Quarter) |>
  ggplot(aes(x = Quarter, y = value, colour = name)) +
  geom_line() +
  labs(title = "Sales, AdBudget, and GDP (no faceting)", x = "Quarter", y = "")
```



Answer: Without faceting (and a shared y-axis), the largest-scale series visually dominates and the smaller-scale series become difficult to compare.

4 USgas: annual natural gas consumption by state (New England)

4.1 Create a tsibble from `us_total` (year index, state key)

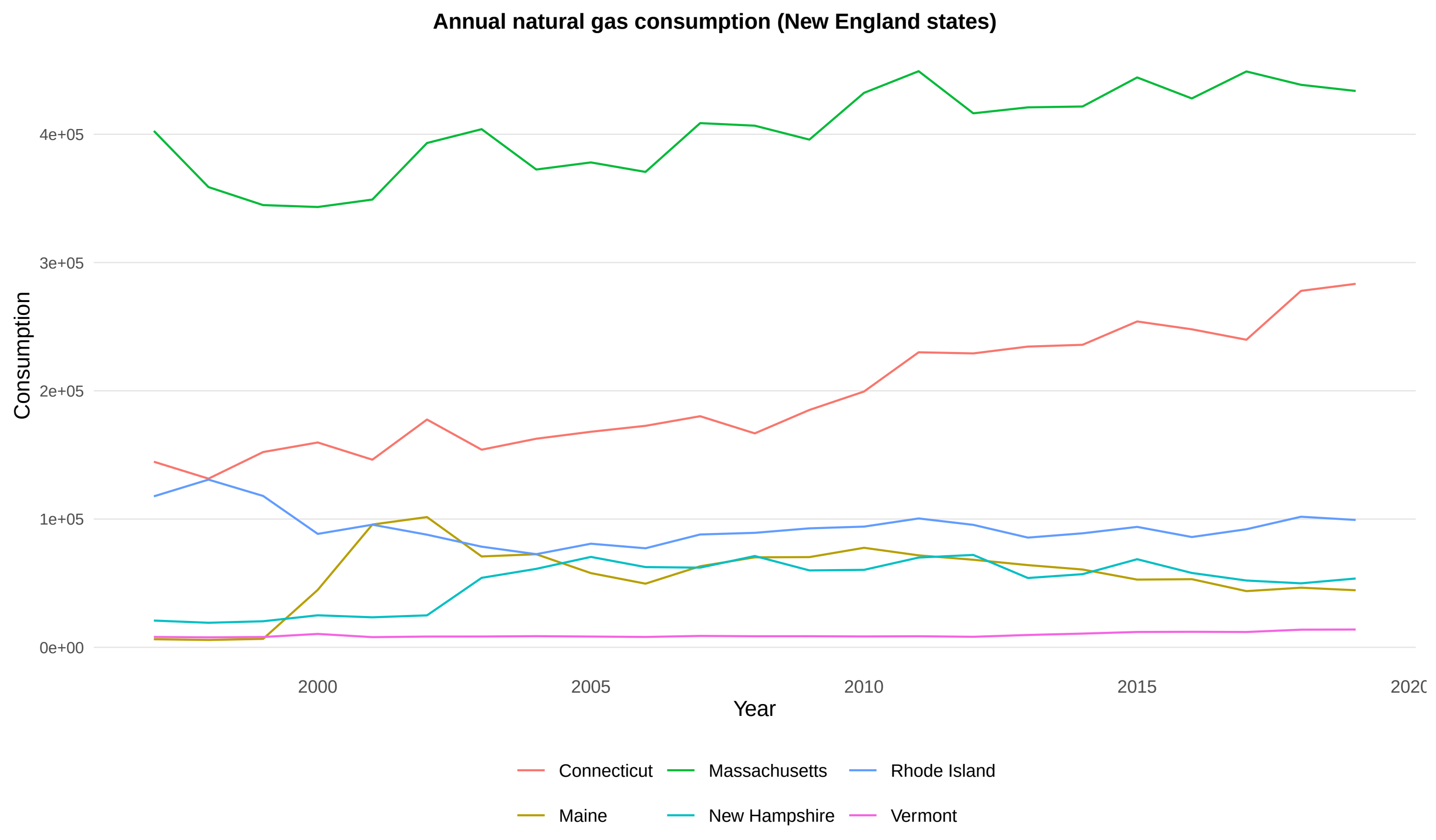
```r
data("us_total", package = "USgas")

gas_ts <- us_total |>
  as_tsibble(index = year, key = state)

gas_ts
```

```
## # A tsibble: 1,266 x 3 [1Y]
## # Key:       state [53]
##     year state        y
##    <int> <chr>    <int>
##  1  1997 Alabama 324158
##  2  1998 Alabama 329134
##  3  1999 Alabama 337270
##  4  2000 Alabama 353614
##  5  2001 Alabama 332693
##  6  2002 Alabama 379343
## 7   2003 Alabama 350345
## 8   2004 Alabama 382367
## 9   2005 Alabama 353156
## 10  2006 Alabama 391093
## # i 1,256 more rows
```

4.2 Plot New England states

New England = Maine, Vermont, New Hampshire, Massachusetts, Connecticut, Rhode Island.

```
new_england <- c("Maine", "Vermont", "New Hampshire",
                 "Massachusetts", "Connecticut", "Rhode Island")

gas_ts |>
  filter(state %in% new_england) |>
  autoplot(y) +
  labs(
    title = "Annual natural gas consumption (New England states)",
    x = "Year",
    y = "Consumption"
  )
```



5 tourism.xlsx: recreate `tourism` tsibble and summaries

5.1 Download and read tourism.xlsx

```r
tourism_url <- "https://otexts.com/fpp3/extrafiles/tourism.xlsx"
tourism_file <- tempfile(fileext = ".xlsx")

download.file(tourism_url, tourism_file, mode = "wb")

tourism_raw <- readxl::read_excel(tourism_file)

dplyr::glimpse(tourism_raw)
```

```
## Rows: 24,320
## Columns: 5
## $ Quarter <chr> "1998-01-01", "1998-04-01", "1998-07-01", "1998-10-01", "1999-~
## $ Region  <chr> "Adelaide", "Adelaide", "Adelaide", "Adelaide", "Adelaide", "A~
## $ State   <chr> "South Australia", "South Australia", "South Australia", "Sout~
## $ Purpose <chr> "Business", "Business", "Business", "Business", "Business", "B~
## $ Trips   <dbl> 135.0777, 109.9873, 166.0347, 127.1605, 137.4485, 199.9126, 16~
```

5.2 Create a tsibble identical in structure to `tsibble::tourism`

```r
tourism_ts <- tourism_raw |>
  mutate(Quarter = yearquarter(Quarter)) |>
  as_tsibble(
    index = Quarter,
    key = c(State, Region, Purpose)
  )

tourism_ts
```

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:       State, Region, Purpose [304]
##    Quarter Region   State Purpose  Trips
##      <qtr> <chr>    <chr> <chr>    <dbl>
##  1 1998 Q1 Canberra ACT   Business 150.
##  2 1998 Q2 Canberra ACT   Business  99.9
##  3 1998 Q3 Canberra ACT   Business 130.
##  4 1998 Q4 Canberra ACT   Business 102.
##  5 1999 Q1 Canberra ACT   Business  95.5
##  6 1999 Q2 Canberra ACT   Business 229.
##  7 1999 Q3 Canberra ACT   Business 109.
##  8 1999 Q4 Canberra ACT   Business 159.
##  9 2000 Q1 Canberra ACT   Business 105.
## 10 2000 Q2 Canberra ACT   Business 202.
## # i 24,310 more rows
```

5.3 Ensure temporal ordering for each Region/Purpose

```r
tourism_ts <- tourism_ts |>
  arrange(Region, Purpose, Quarter)
```

5.4 Region–Purpose combination with maximum average overnight trips

```r
max_region_purpose <- tourism_ts |>
  group_by(Region, Purpose) |>
  summarise(avg_trips = mean(Trips, na.rm = TRUE), .groups = "drop") |>
  arrange(desc(avg_trips)) |>
  slice(1)

max_region_purpose
```

```
## # A tsibble: 1 x 4 [1Q]
## # Key:       Region, Purpose [1]
##   Region    Purpose  Quarter avg_trips
##   <chr>     <chr>      <qtr>     <dbl>
## 1 Melbourne Visiting 2017 Q4      985.
```

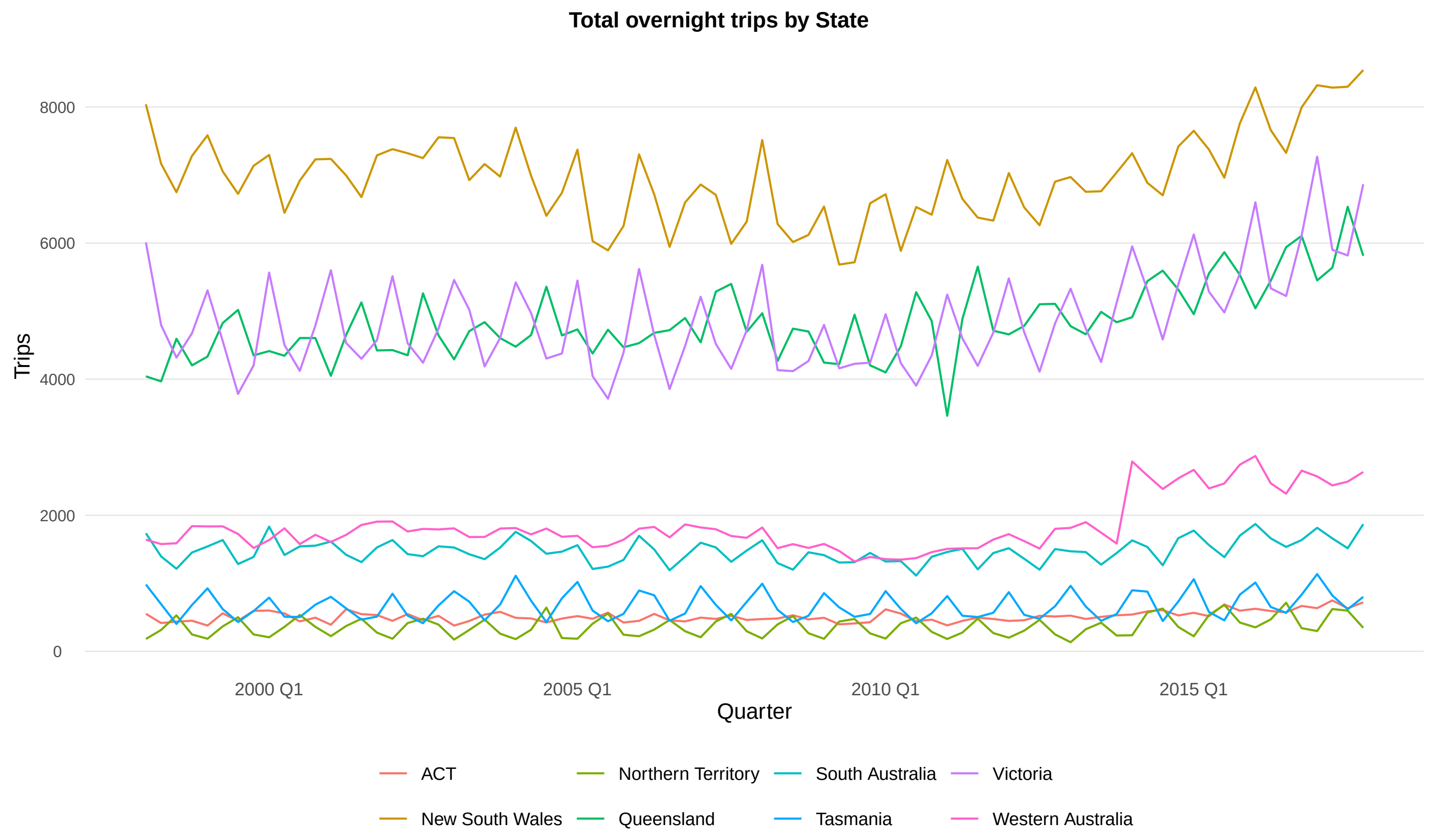
Answer: The row above identifies the `(Region, Purpose)` combination with the greatest mean `Trips`.

5.5 Total trips by State (combining Region and Purpose)

```r
tourism_state_total <- tourism_ts |>
  index_by(Quarter) |>
  group_by(State) |>
  summarise(Trips = sum(Trips, na.rm = TRUE)) |>
  as_tsibble(index = Quarter, key = State)

tourism_state_total
```

```
## # A tsibble: 640 x 3 [1Q]
## # Key:       State [8]
##    State Quarter Trips
##    <chr>   <qtr> <dbl>
##  1 ACT   1998 Q1  551.
##  2 ACT   1998 Q2  416.
##  3 ACT   1998 Q3  436.
##  4 ACT   1998 Q4  450.
##  5 ACT   1999 Q1  379.
##  6 ACT   1999 Q2  558.
##  7 ACT   1999 Q3  449.
##  8 ACT   1999 Q4  595.
##  9 ACT   2000 Q1  600.
## 10 ACT   2000 Q2  557.
## # i 630 more rows
```

```
tourism_state_total |>
  autoplot(Trips) +
  labs(title = "Total overnight trips by State", x = "Quarter", y = "Trips")
```

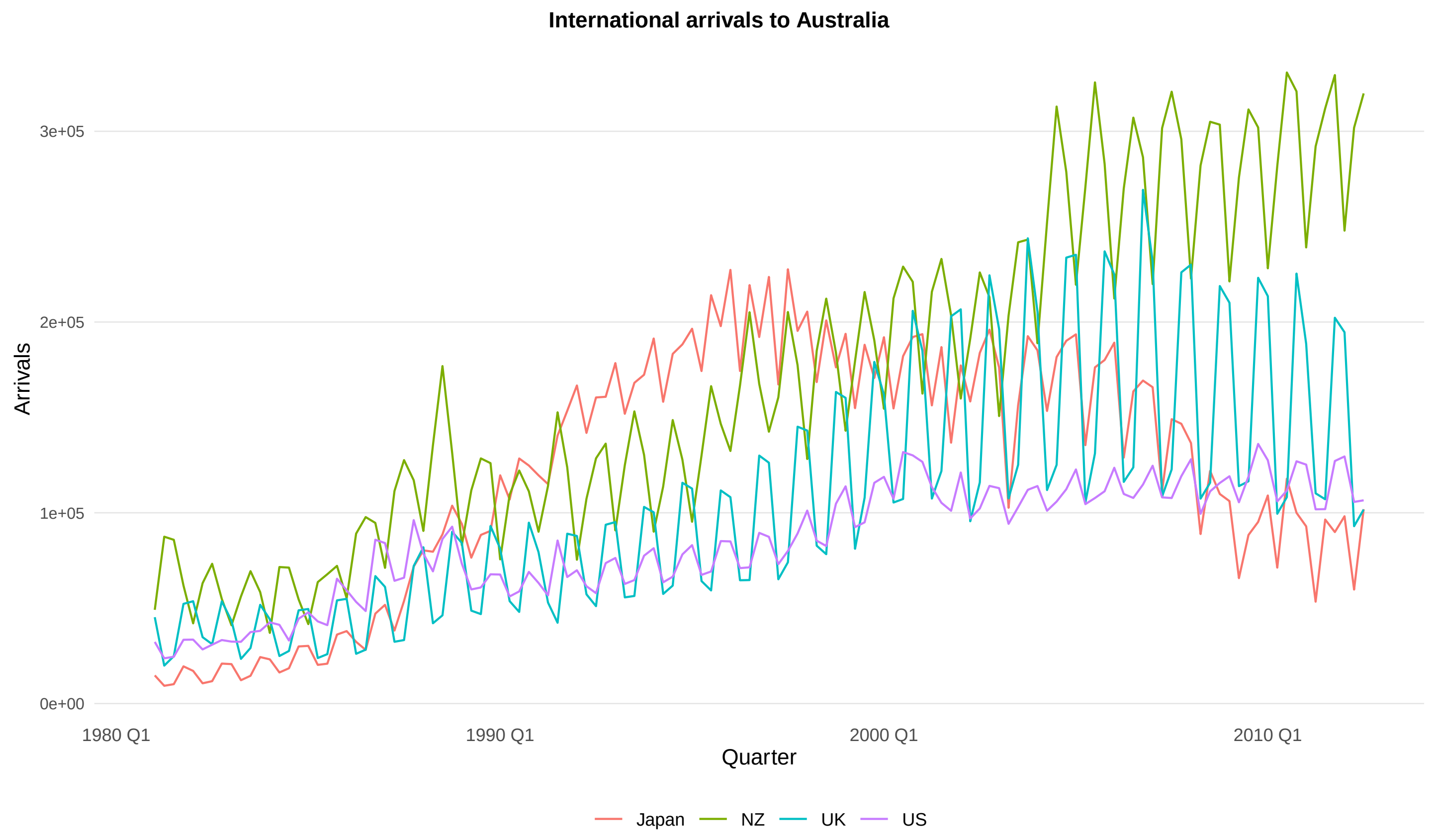


6 aus_arrivals: compare arrivals from Japan, NZ, UK, US

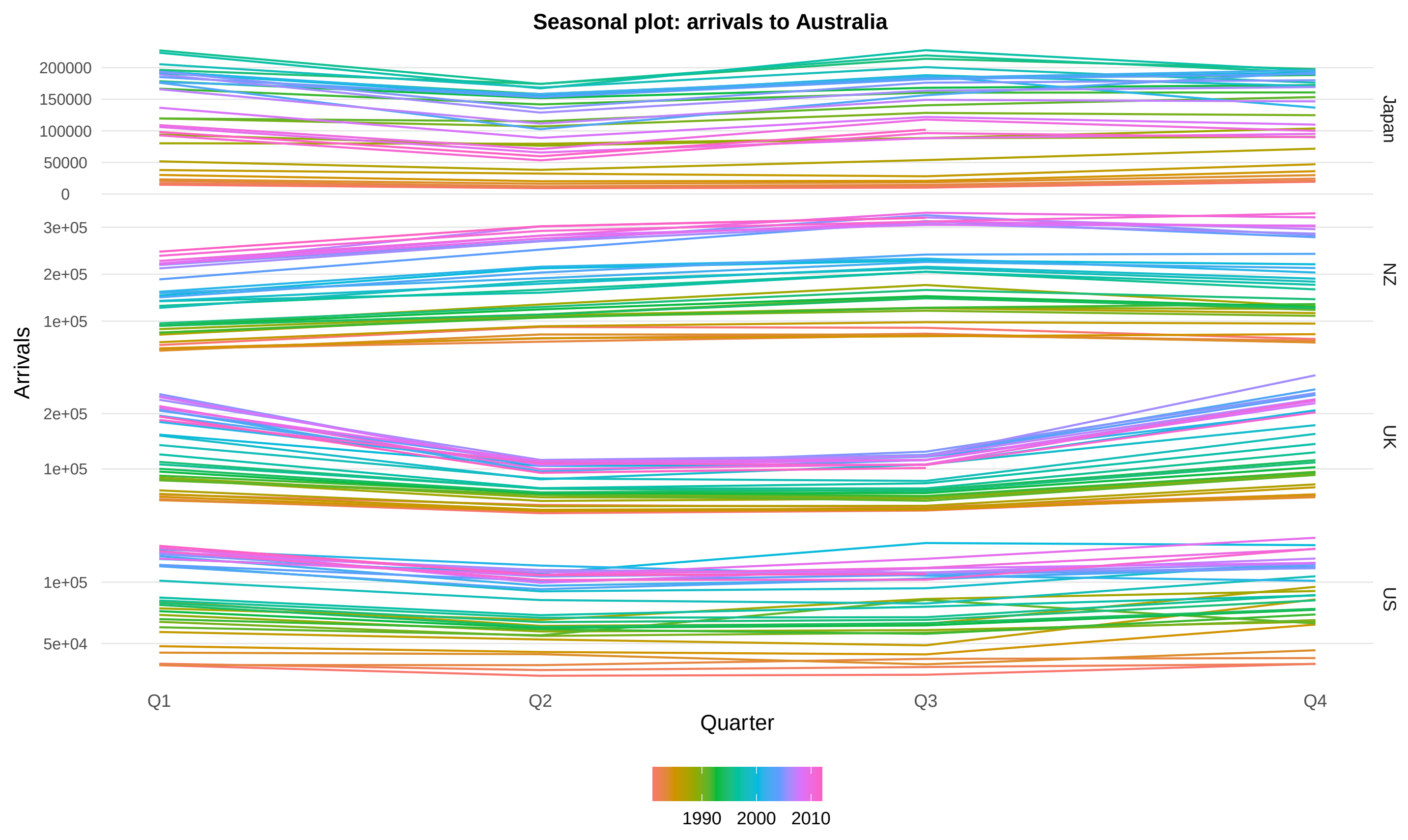
(JUST FOR FUN)

Use `autoplot()`, `gg_season()`, and `gg_subseries()`.

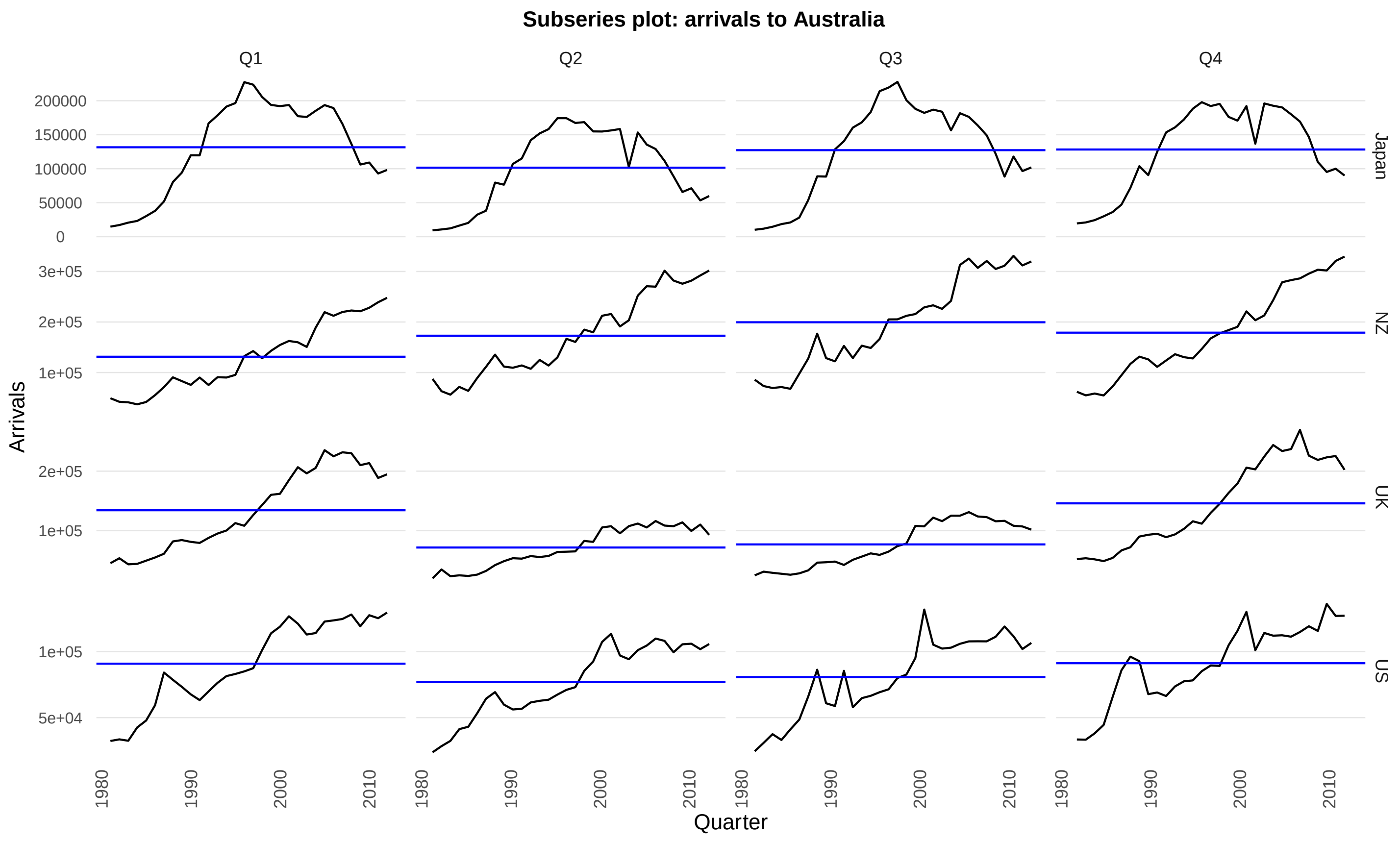
```
aus_arrivals |>
  autoplot(Arrivals) +
  labs(title = "International arrivals to Australia", x = "Quarter", y = "Arrivals")
```



```r
aus_arrivals |>
  gg_season(Arrivals) +
  labs(title = "Seasonal plot: arrivals to Australia", y = "Arrivals")
```



```r
aus_arrivals |>
  gg_subseries(Arrivals) +
  labs(title = "Subseries plot: arrivals to Australia", y = "Arrivals")
```



Answer (unusual observations):
The subseries plot highlights deviations from the typical seasonal pattern by showing each quarter separately over time. Japan exhibits unusually low arrivals in Q2 and Q3 during later years, deviating sharply from its normally strong seasonal structure. The United States shows occasional Q3 spikes that exceed the typical seasonal range, indicating one-off surges rather than regular seasonality. The UK also displays increased variability in Q3 and Q4, with some years standing out as unusually high. In contrast, New Zealand arrivals remain relatively stable across all quarters, with no clear unusual observations.

7 aus_retail: sample a series and explore

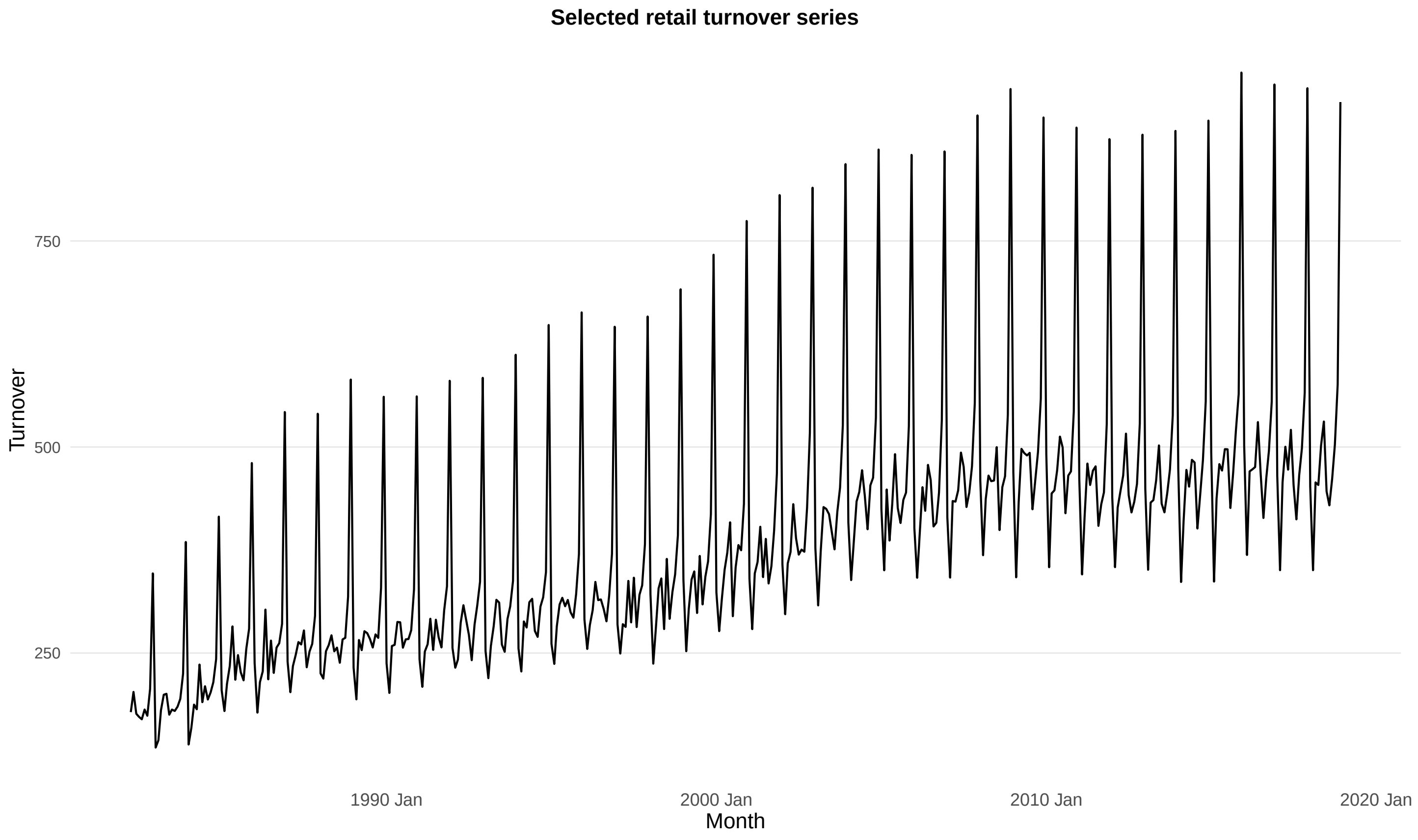
(JUST FOR FUN)

```r
set.seed(67)
myseries <- aus_retail |>
  filter(`Series ID` == sample(aus_retail$`Series ID`, 1))

myseries |> dplyr::glimpse()
```

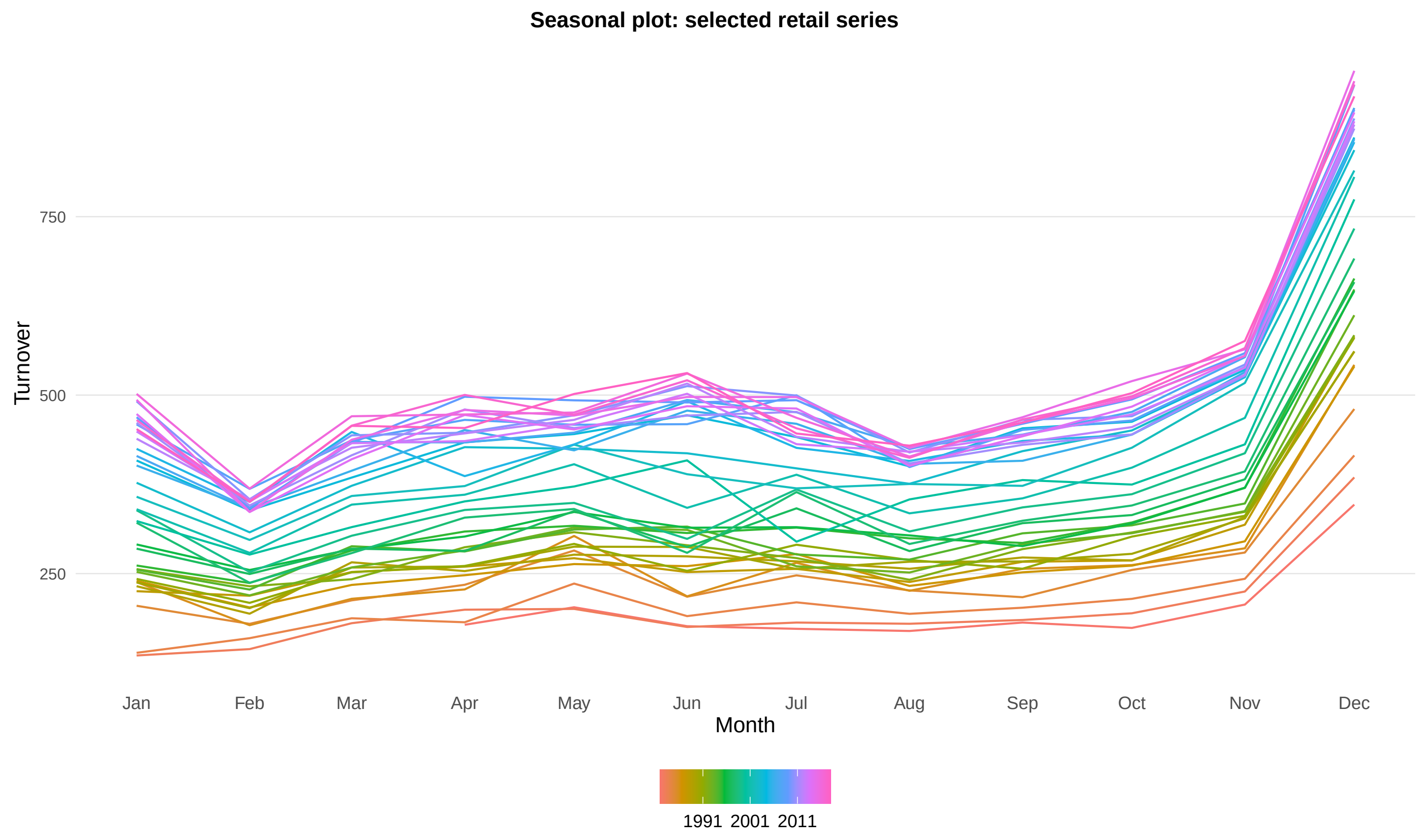
```
## Rows: 441
## Columns: 5
## Key: State, Industry [1]
## $ State       <chr> "New South Wales", "New South Wales", "New South Wales", "~
## $ Industry    <chr> "Department stores", "Department stores", "Department stor~
## $ `Series ID` <chr> "A3349790V", "A3349790V", "A3349790V", "A3349790V", "A3349~
## $ Month       <mth> 1982 Apr, 1982 May, 1982 Jun, 1982 Jul, 1982 Aug, 1982 Sep~
## $ Turnover    <dbl> 178.3, 202.8, 176.3, 172.6, 169.6, 181.4, 173.9, 206.6, 34~
```

7.1 Graphics exploration

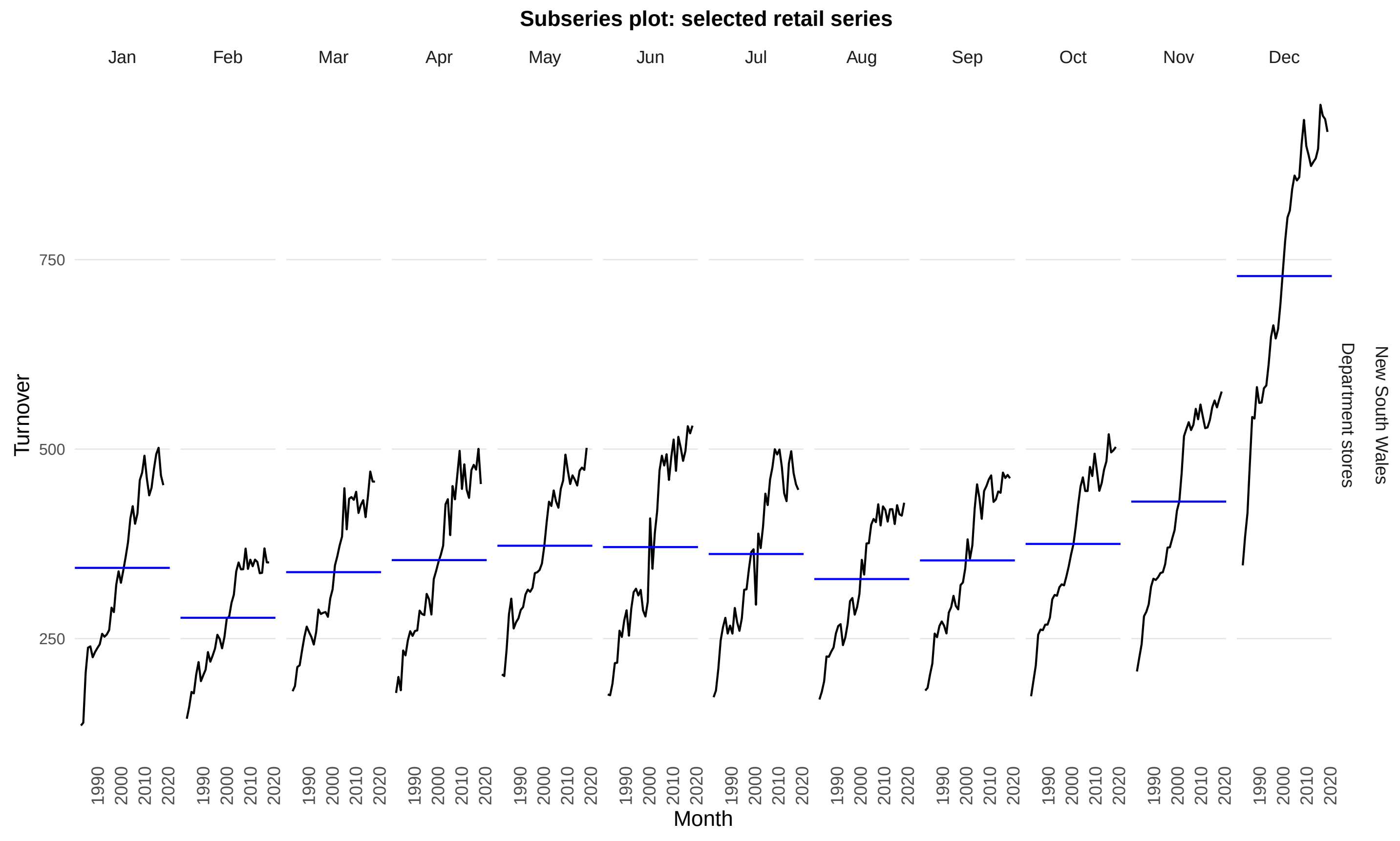
```r
myseries |>
  autoplot(Turnover) +
  labs(title = "Selected retail turnover series", x = "Month", y = "Turnover")
```



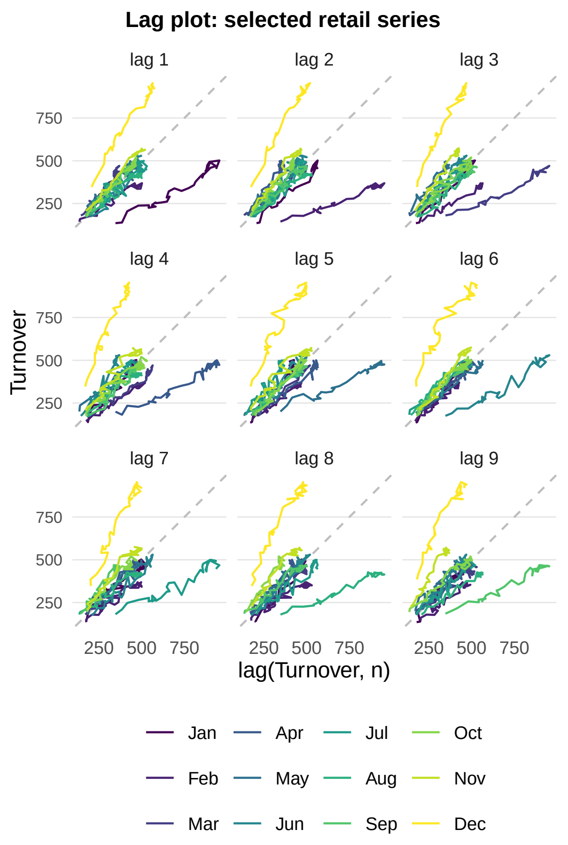
```r
myseries |>
  gg_season(Turnover) +
  labs(title = "Seasonal plot: selected retail series", y = "Turnover")
```



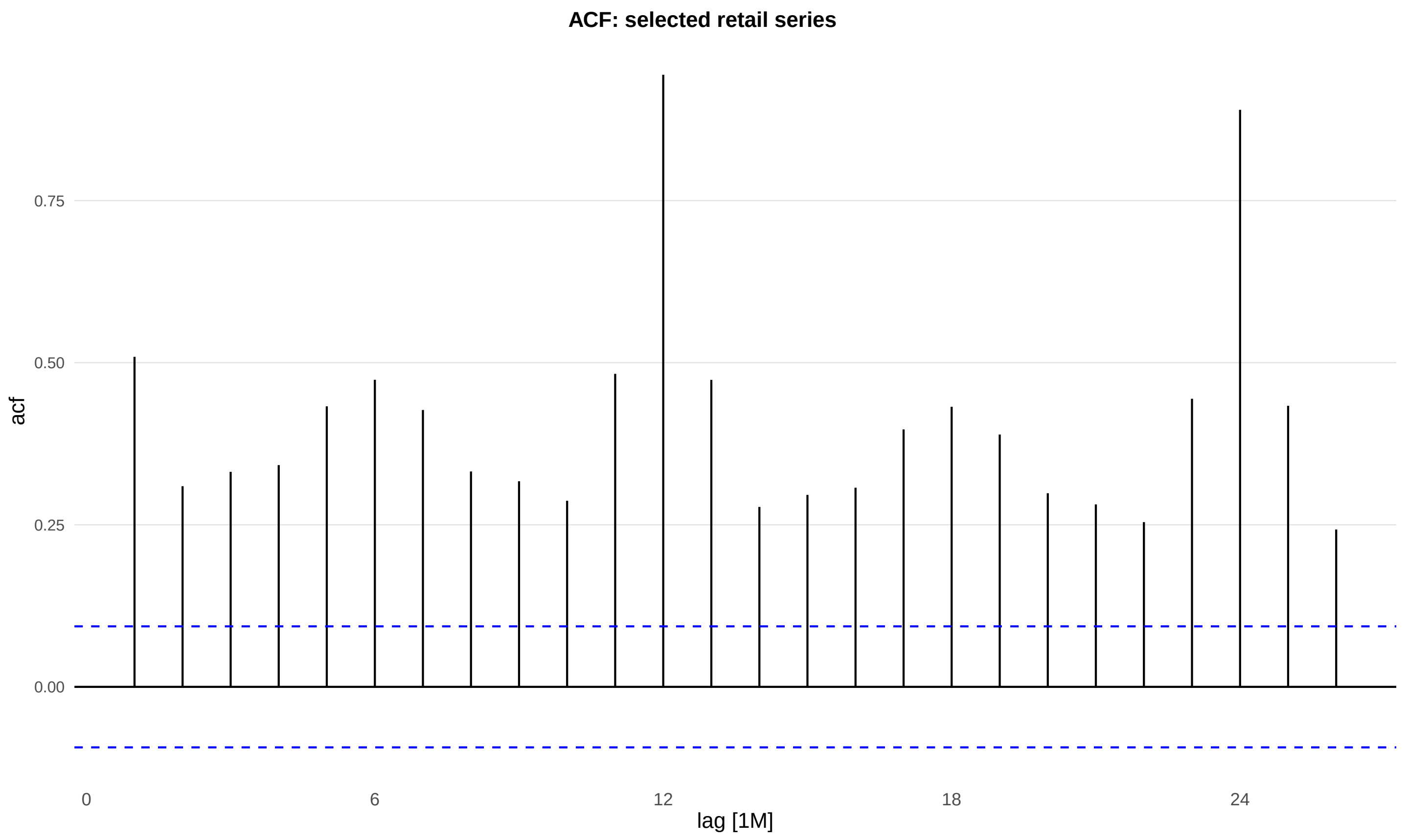
```r
myseries |>
  gg_subseries(Turnover) +
  labs(title = "Subseries plot: selected retail series", y = "Turnover")
```



```
myseries |>
  gg_lag(Turnover) +
  labs(title = "Lag plot: selected retail series", y = "Turnover")
```



```
myseries |>
  ACF(Turnover) |>
  autoplot() +
  labs(title = "ACF: selected retail series")
```



Answer (seasonality/cyclicity/trend):
- **Seasonality** is indicated by repeating within-year patterns and ACF spikes at seasonal lags (e.g., 12 for monthly data).
- **Trend** appears as persistent long-run increase/decrease and often as slow ACF decay.
- **Cyclicity** shows as multi-year rises/falls not tied to a fixed seasonal frequency.

Use the plots above to describe what is present in *this specific sampled series*.

8 Explore five additional series with common graphics + ACF

Series: - **"Total Private" Employed** from `us_employment` - **Bricks** from `aus_production` - **Hare** from `pelt` - **"H02" Cost** from PBS - **Barrels** from `us_gasoline`

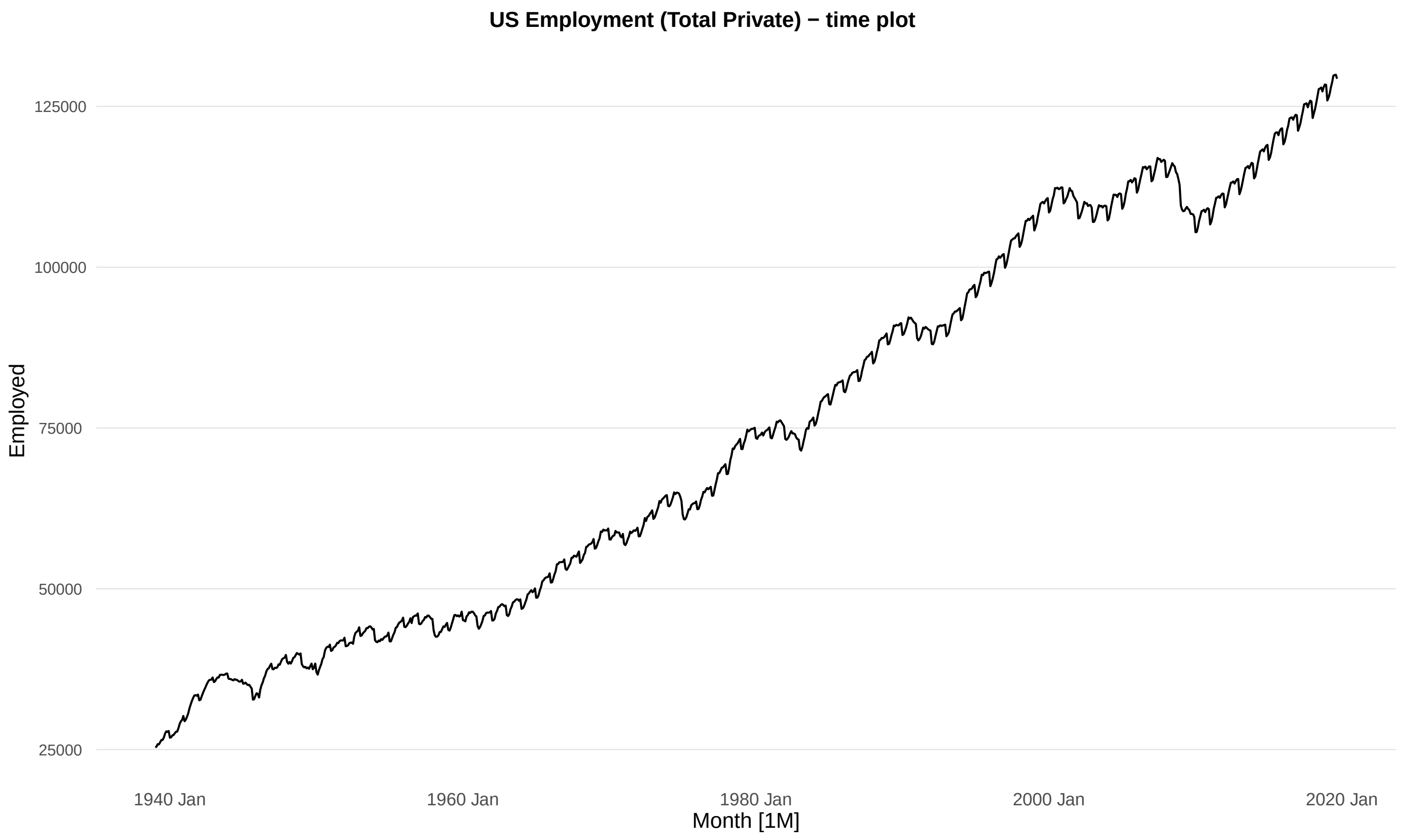
```
emp_private <- us_employment |>
  filter(Title == "Total Private") |>
  select(Month, Employed)

bricks_ts <- aus_production |> select(Quarter, Bricks)

hare_ts <- pelt_long(pelt) |> filter(Animal == "Hare")

pbs_keys <- key_vars(PBS)

pbs_h02 <- PBS |>
  filter(ATC2 == "H02") |>
  group_by(across(all_of(key_vars(PBS)))) |>
  filter(dplyr::cur_group_id() == 1) |>
```

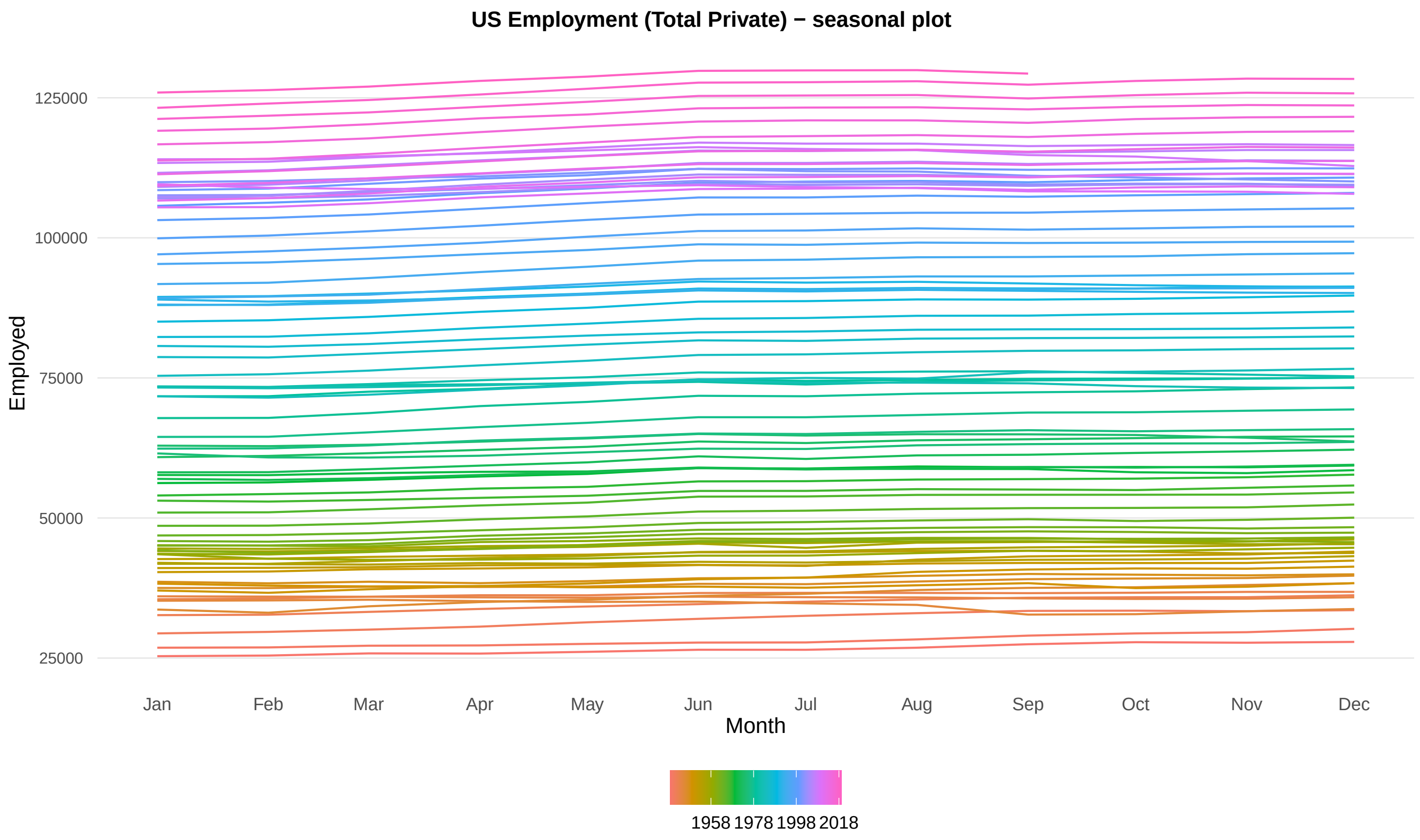
```r
  ungroup() |>
  select(Month, Cost)

gas_barrels <- us_gasoline |> select(Week, Barrels)
```

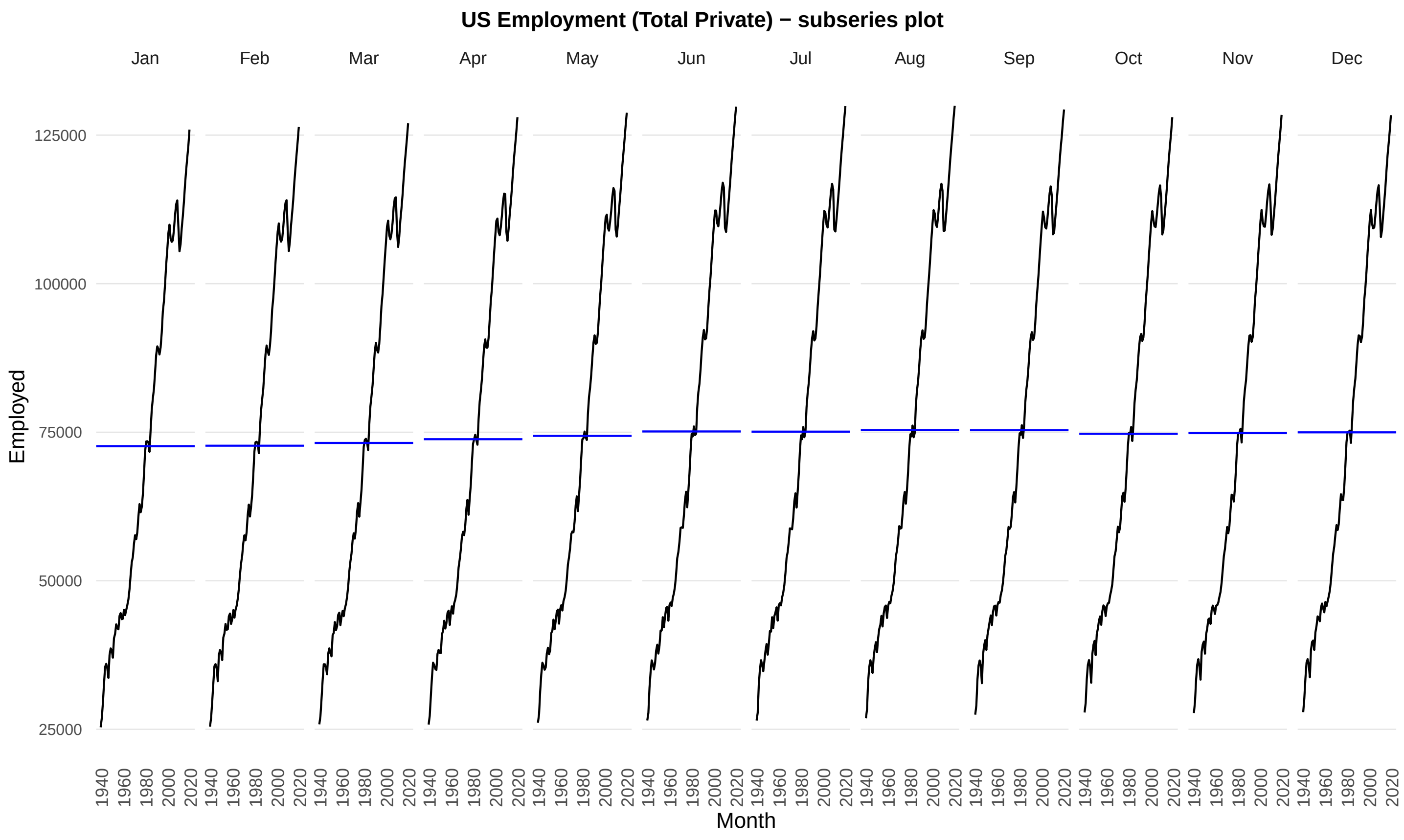
Helper to run the same exploration:

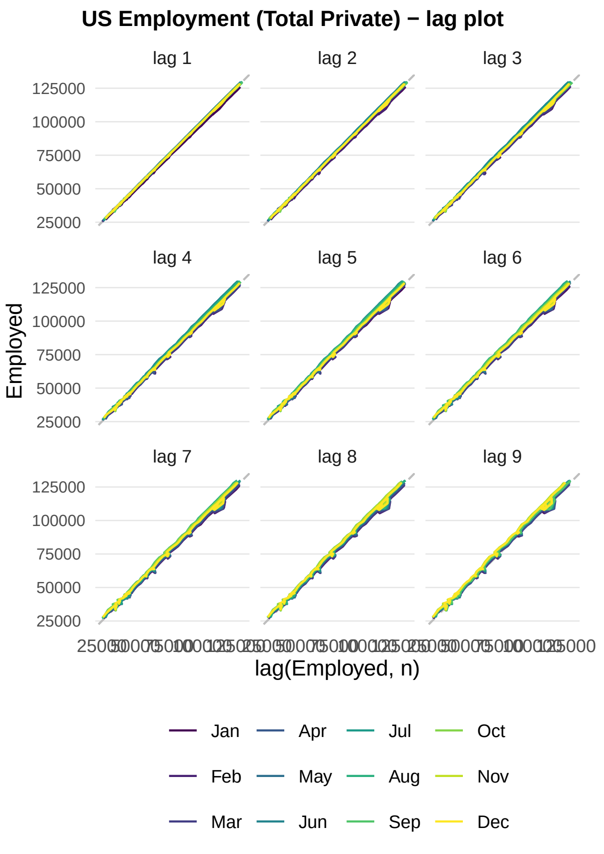
```r
explore_series <- function(data, value_col, title_prefix = "") {
  list(
    time = data |> autoplot({{ value_col }}) +
      labs(title = paste0(title_prefix, " — time plot")),

    season = tryCatch(
      data |> gg_season({{ value_col }}) + labs(title = paste0(title_prefix, " —
↪   seasonal plot")),
      error = function(e) NULL
    ),

    subseries = tryCatch(
      data |> gg_subseries({{ value_col }}) + labs(title = paste0(title_prefix, " —
↪   subseries plot")),
      error = function(e) NULL
    ),

    lag = tryCatch(
      data |> gg_lag({{ value_col }}) + labs(title = paste0(title_prefix, " — lag
↪   plot")),
      error = function(e) NULL
    ),

    acf = data |> ACF({{ value_col }}) |> autoplot() +
      labs(title = paste0(title_prefix, " — ACF"))
  )
}
```

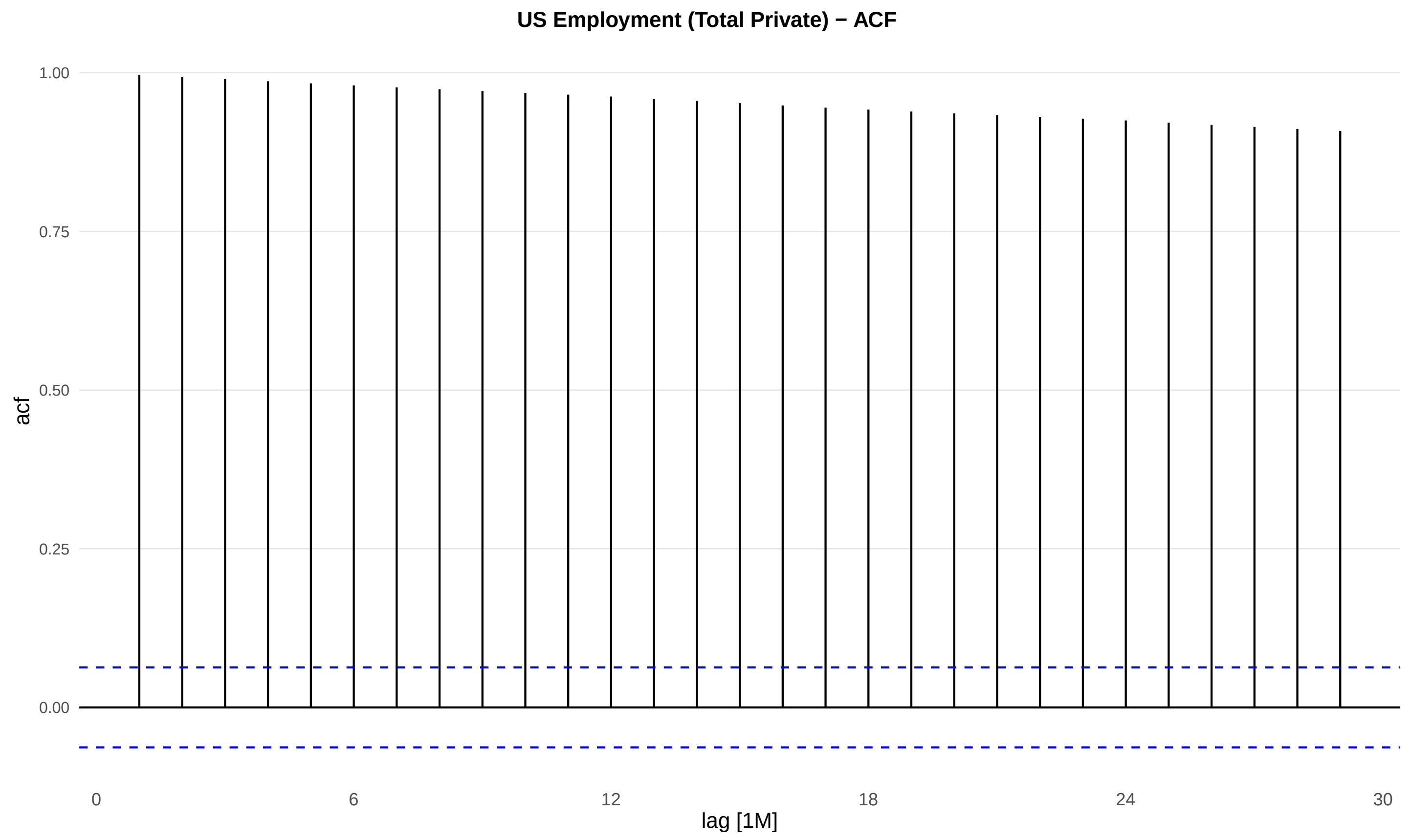
```r
plots_emp <- explore_series(emp_private, Employed, "US Employment (Total Private)")
plots_emp$time; plots_emp$season; plots_emp$subseries; plots_emp$lag; plots_emp$acf
```


US Employment (Total Private) − time plot
125000
100000
75000
50000
25000
Employed
1940 Jan
1960 Jan
1980 Jan
2000 Jan
2020 Jan
Month [1M]

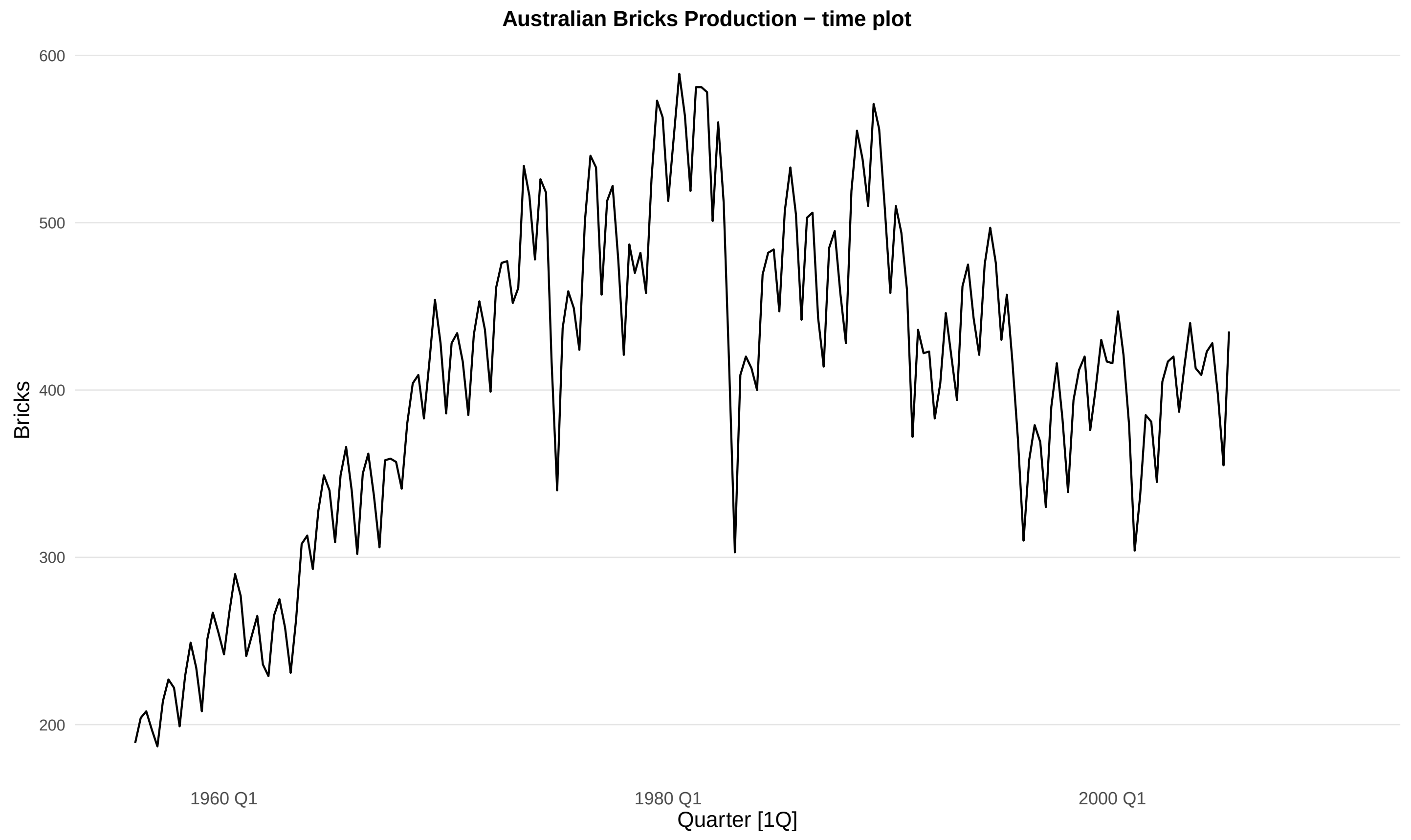

US Employment (Total Private) − seasonal plot
125000
100000
75000
50000
25000
Employed
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
1958
1978
1998
2018

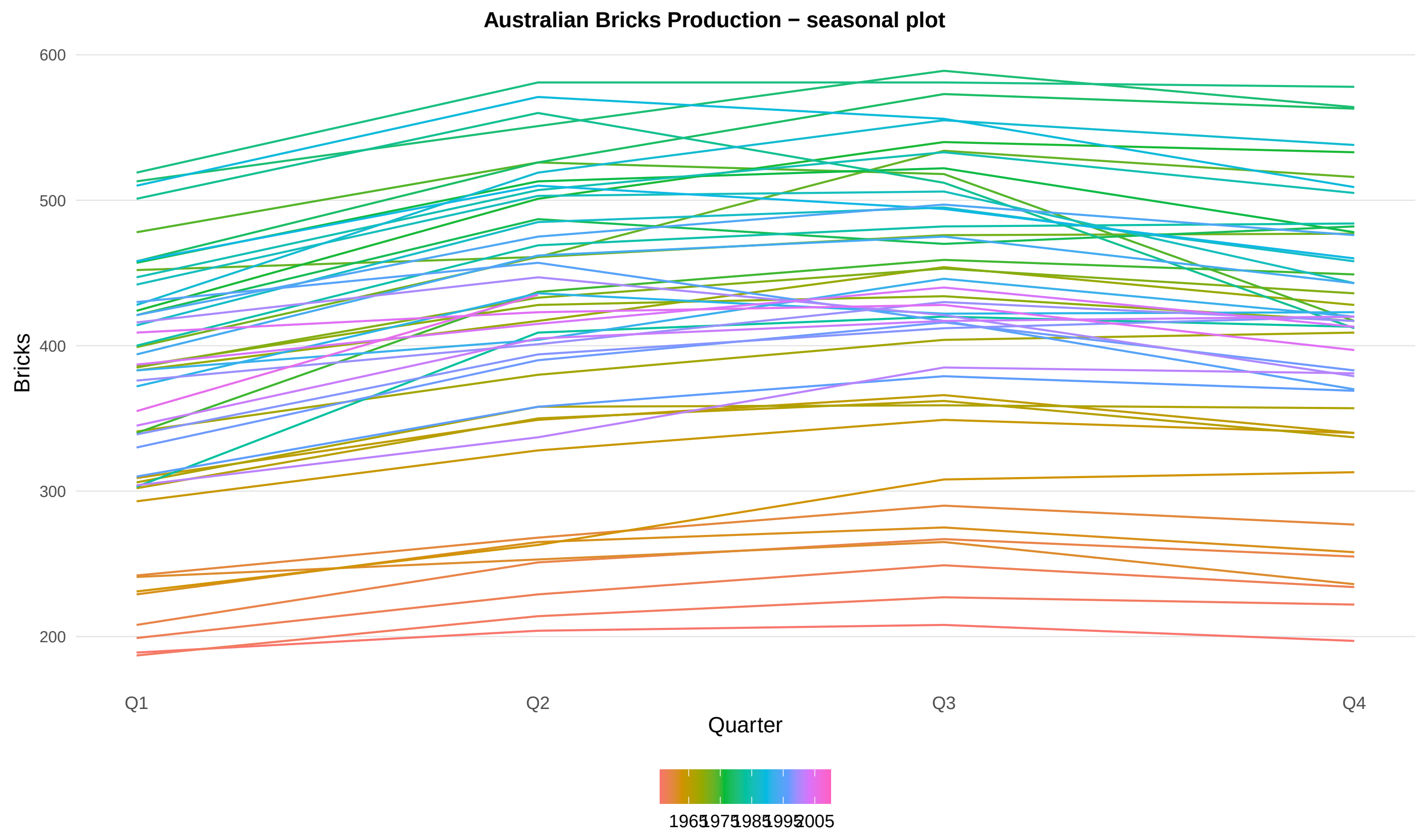

US Employment (Total Private) − subseries plot
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
125000
100000
75000
50000
25000
Employed
1940
1960
1980
2000
2020
Month

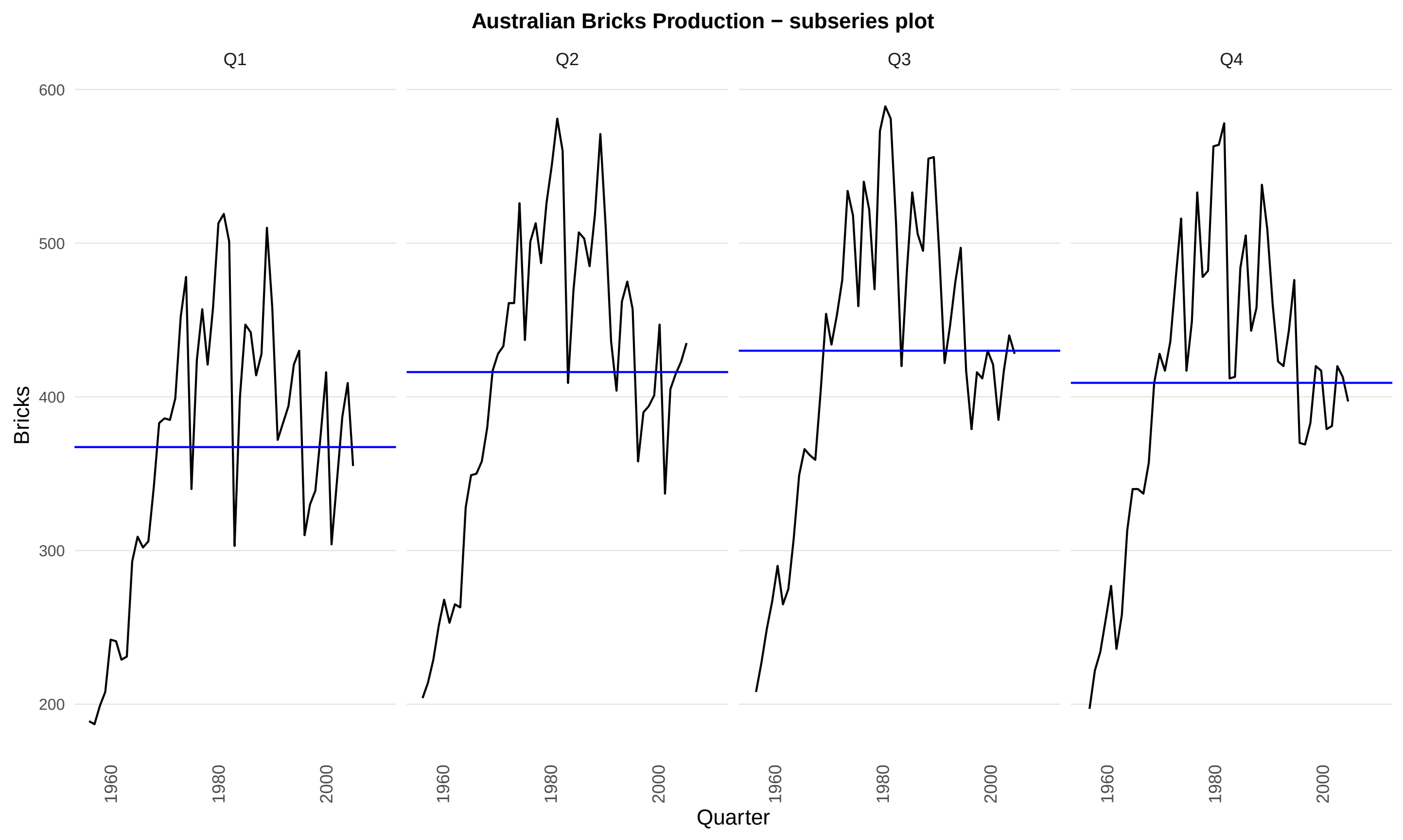

US Employment (Total Private) − lag plot
lag 1
lag 2
lag 3
lag 4
lag 5
lag 6
lag 7
lag 8
lag 9
125000
100000
75000
50000
25000
Employed
lag(Employed, n)
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

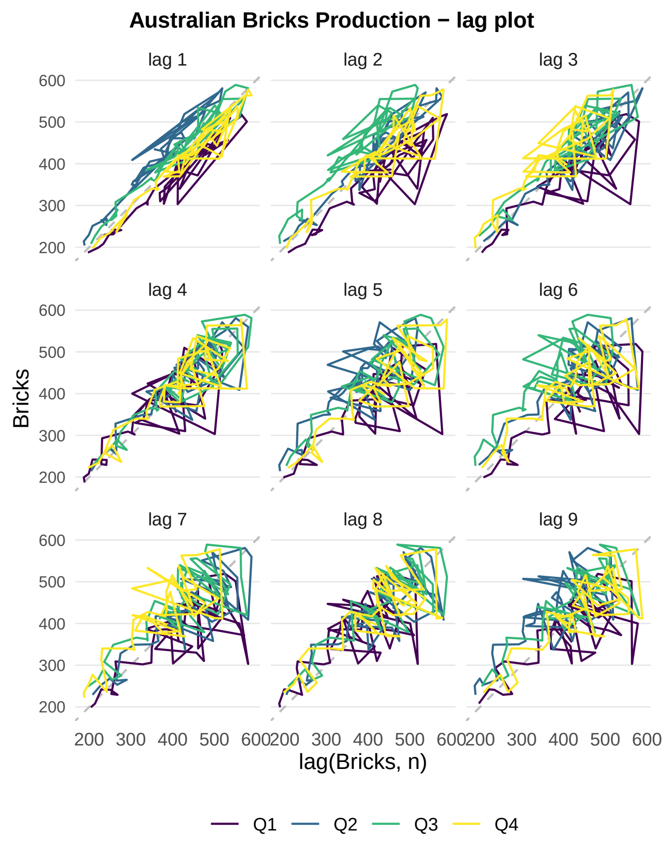


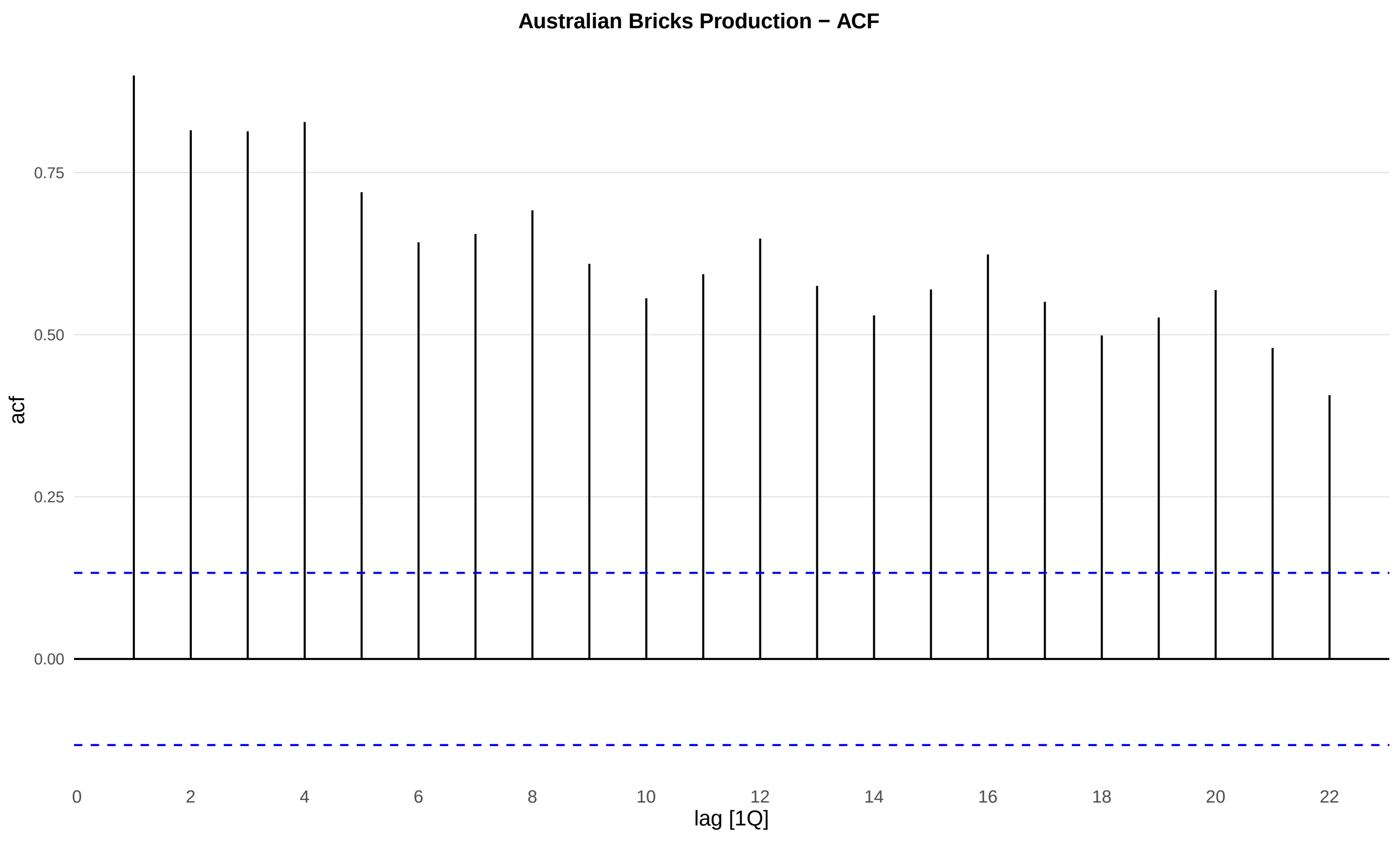
```r
plots_bricks <- explore_series(bricks_ts, Bricks, "Australian Bricks Production")
plots_bricks$time; plots_bricks$season; plots_bricks$subseries; plots_bricks$lag;
↪  plots_bricks$acf
```



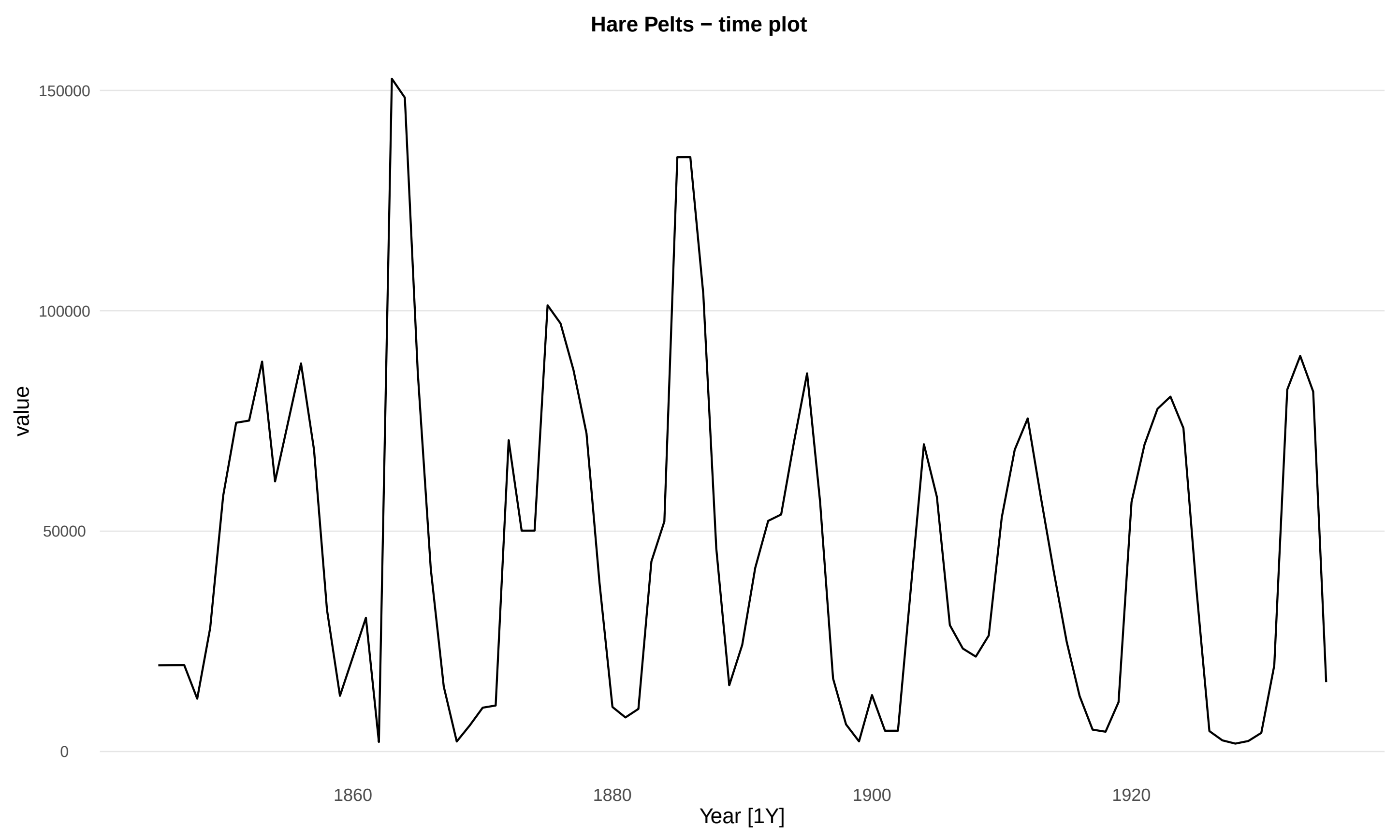

Australian Bricks Production − seasonal plot
600
500
400
300
200
Bricks
Q1
Q2
Q3
Q4
Quarter
1965
1975
1985
1995
2005


Australian Bricks Production − subseries plot
Q1
Q2
Q3
Q4
600
500
400
300
200
Bricks
1960
1980
2000
Quarter

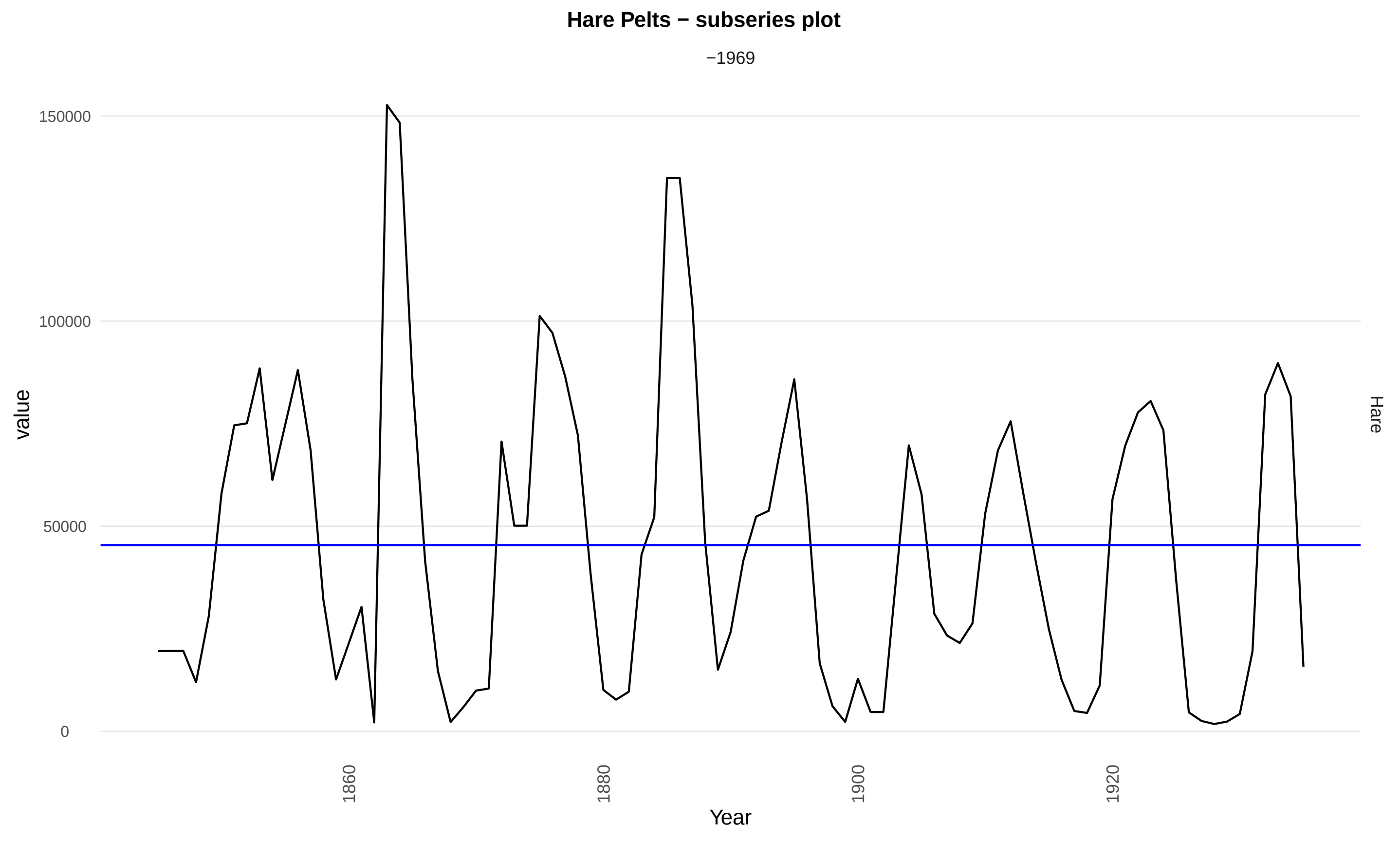


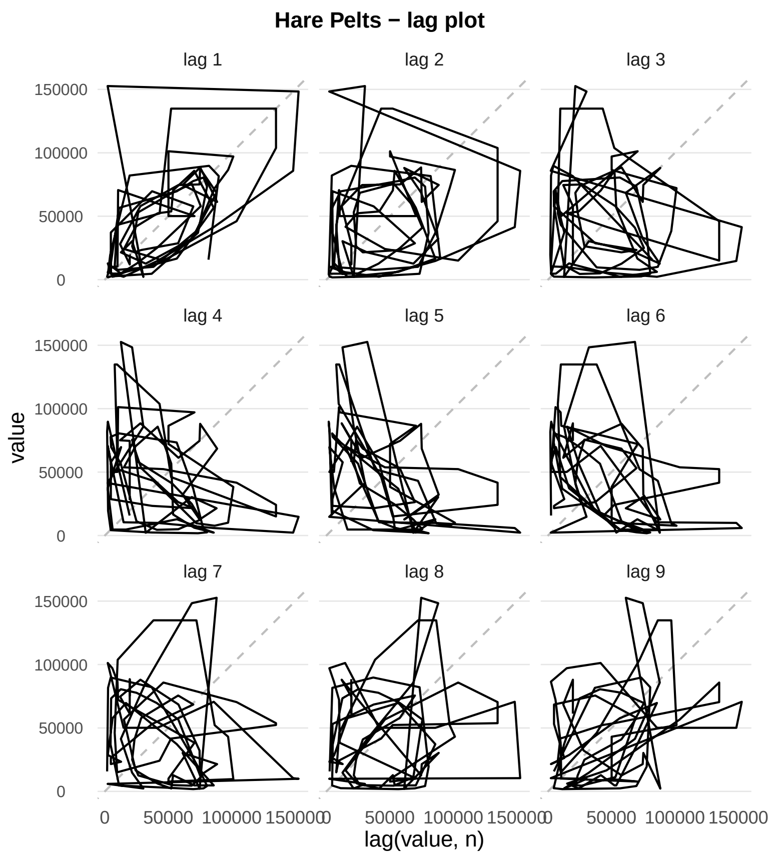


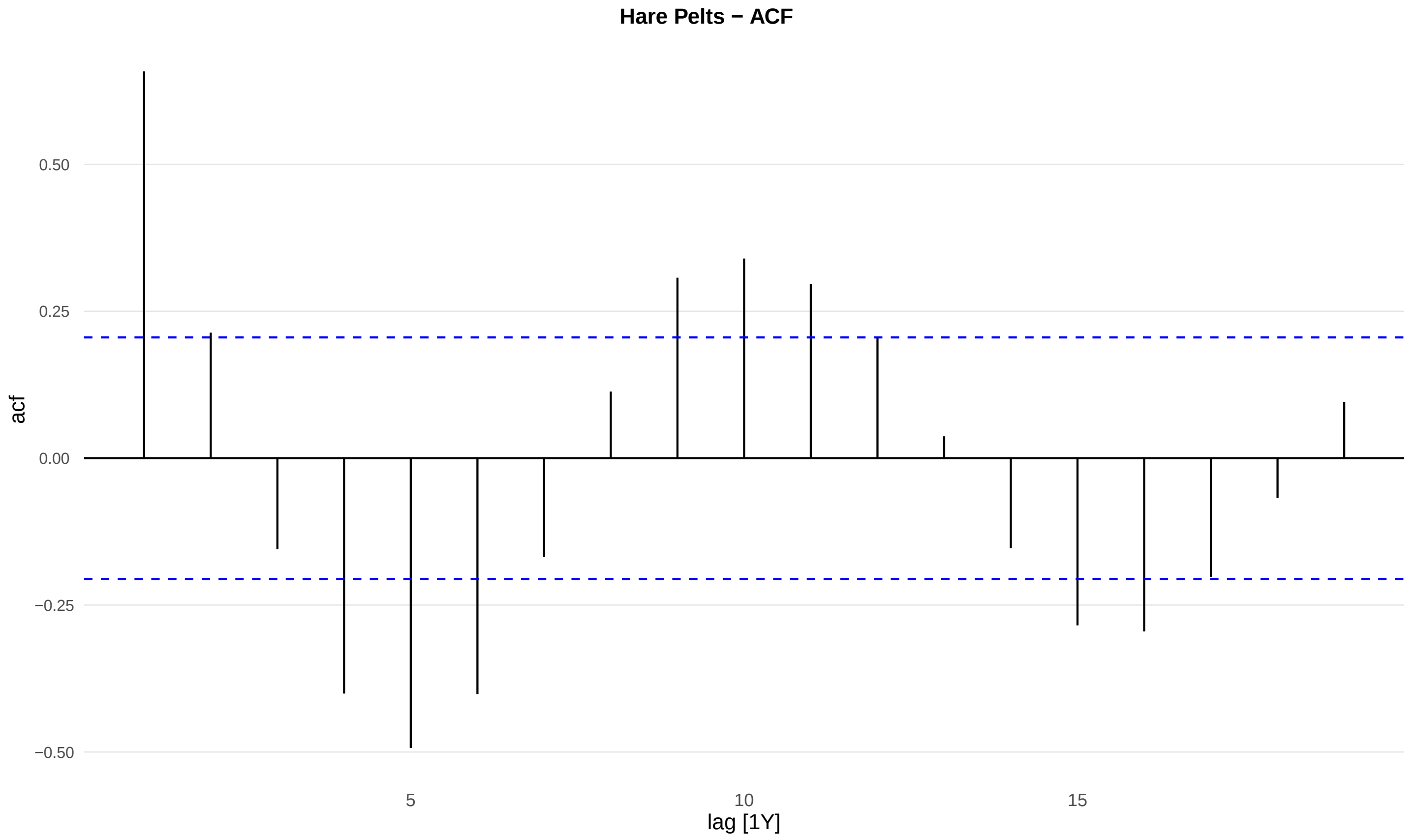
```
plots_hare <- explore_series(hare_ts, value, "Hare Pelts")
plots_hare$time; plots_hare$season; plots_hare$subseries; plots_hare$lag;
↪  plots_hare$acf
```


Hare Pelts − time plot
150000
100000
50000
0
value
1860
1880
1900
1920
Year [1Y]

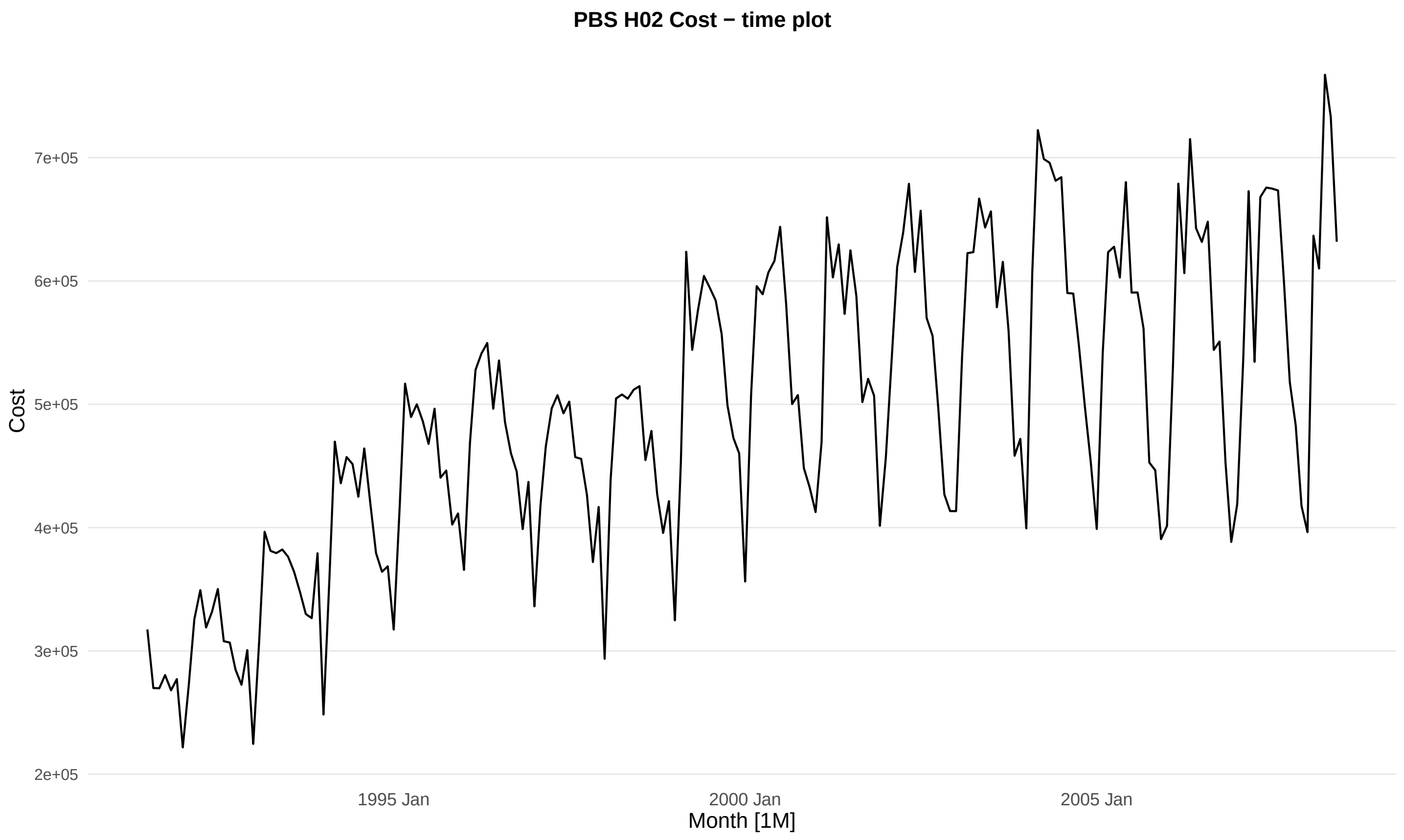
```
## NULL
```

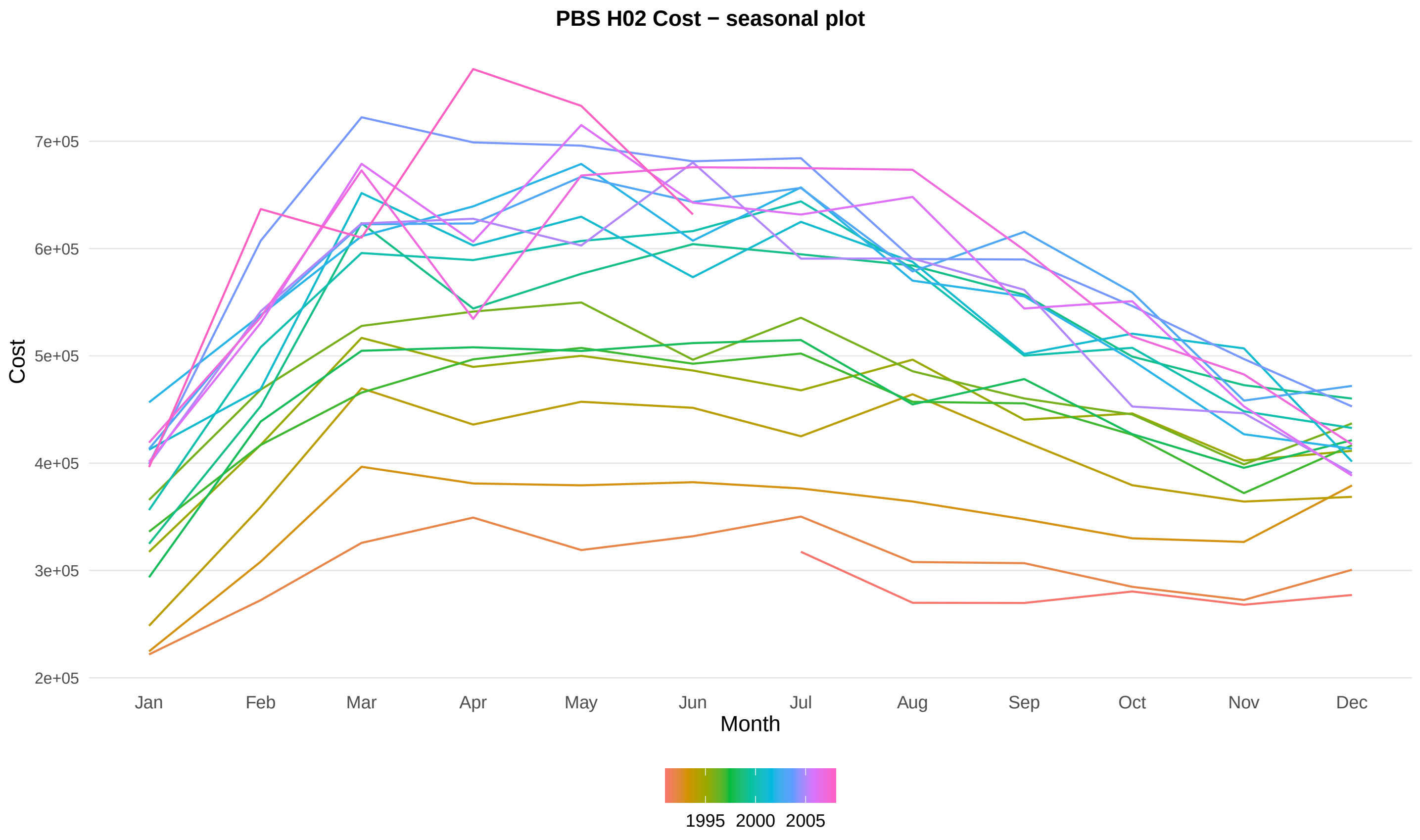

Hare Pelts − subseries plot
−1969
150000
100000
50000
0
value
Hare
1860
1880
1900
1920
Year

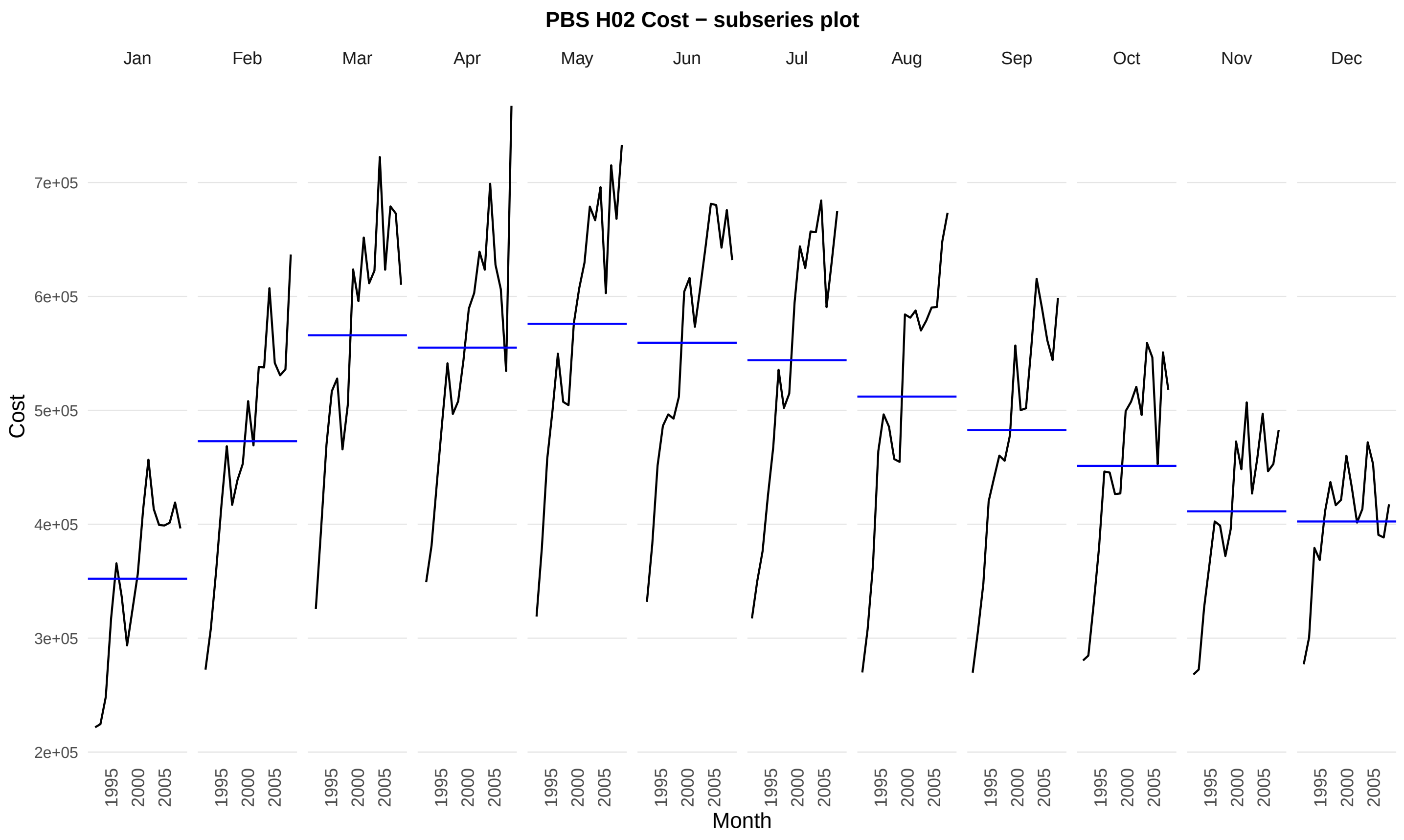


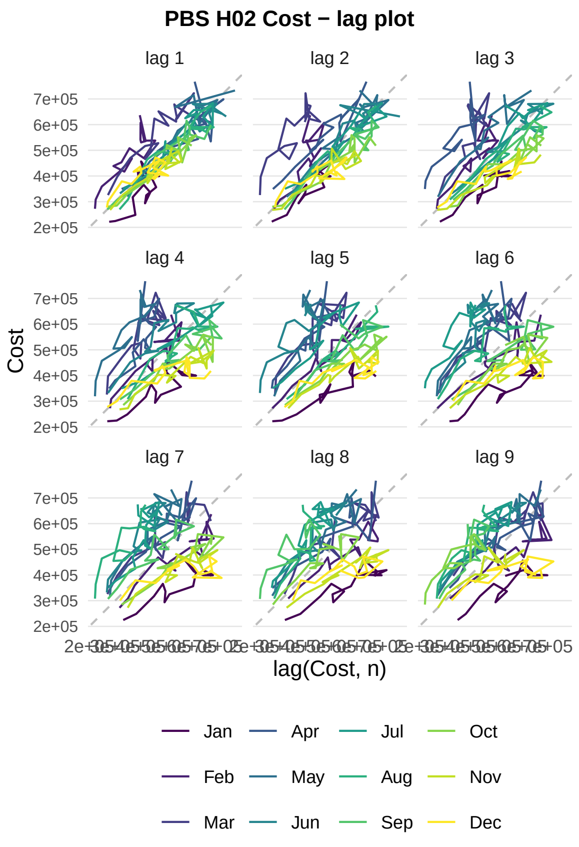


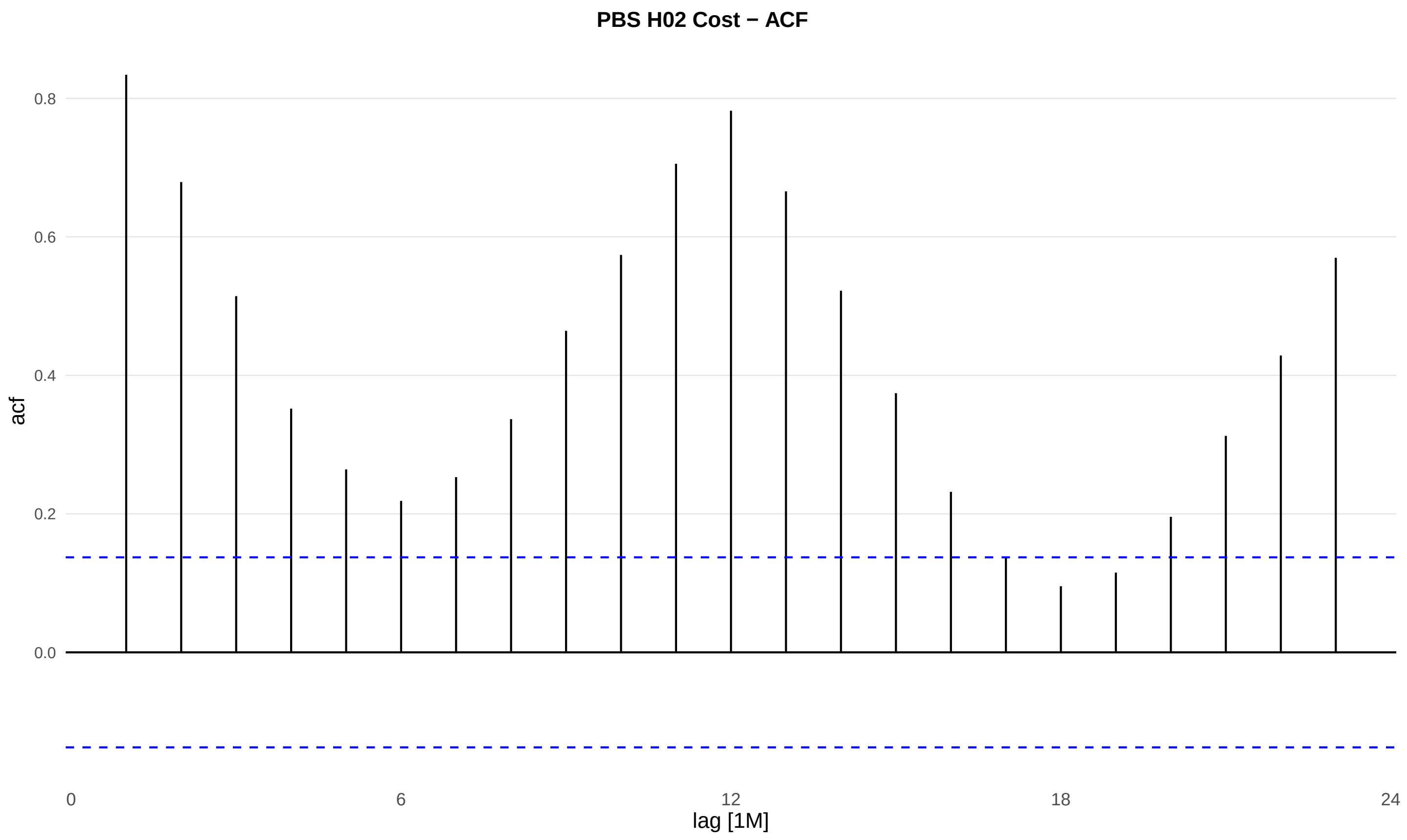
```
plots_pbs <- explore_series(pbs_h02, Cost, "PBS H02 Cost")
plots_pbs$time; plots_pbs$season; plots_pbs$subseries; plots_pbs$lag; plots_pbs$acf
```


PBS H02 Cost − time plot
Cost
7e+05
6e+05
5e+05
4e+05
3e+05
2e+05
1995 Jan
2000 Jan
2005 Jan
Month [1M]

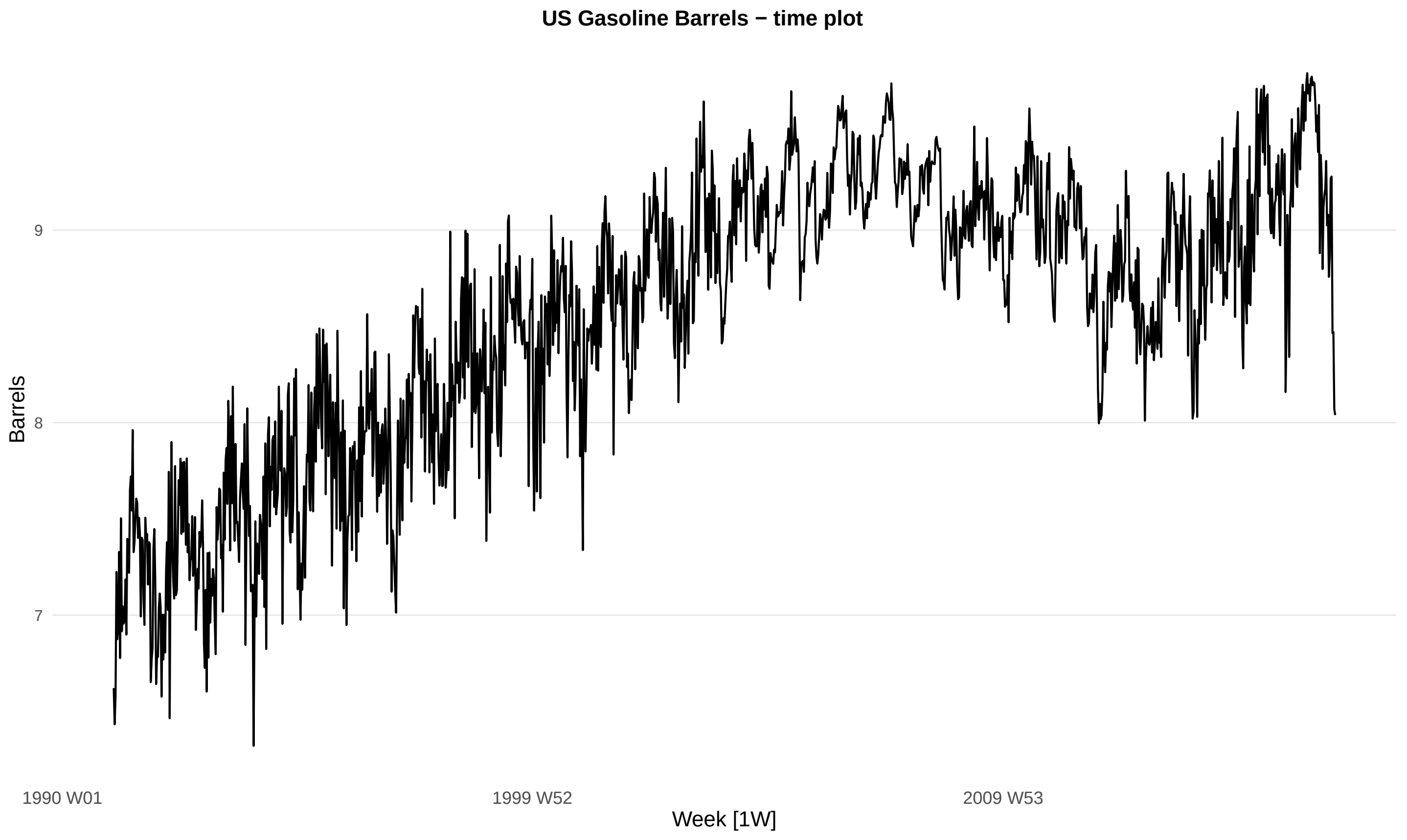

PBS H02 Cost − seasonal plot
Cost
7e+05
6e+05
5e+05
4e+05
3e+05
2e+05
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
1995
2000
2005

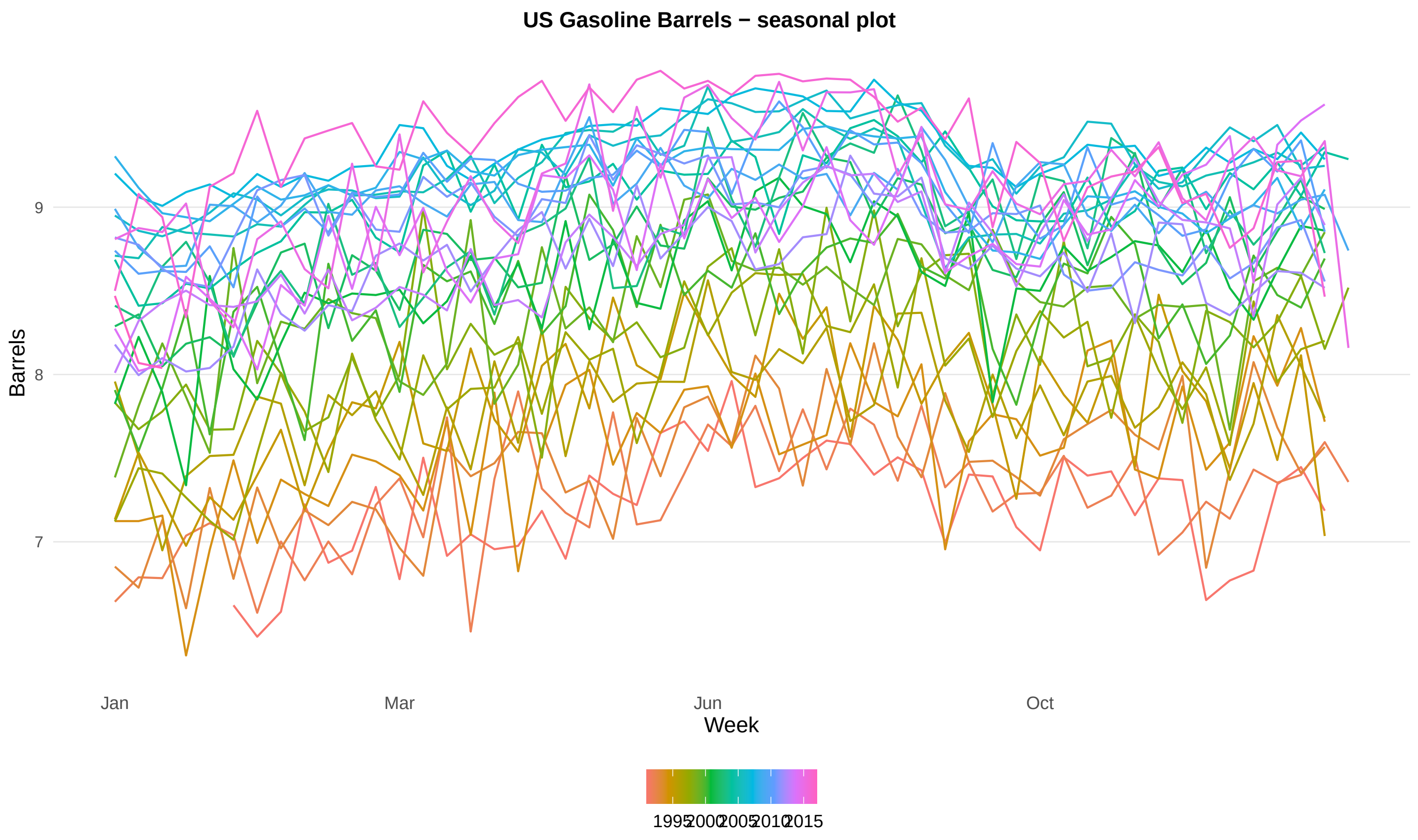

PBS H02 Cost − subseries plot
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Cost
7e+05
6e+05
5e+05
4e+05
3e+05
2e+05
1995
2000
2005
Month

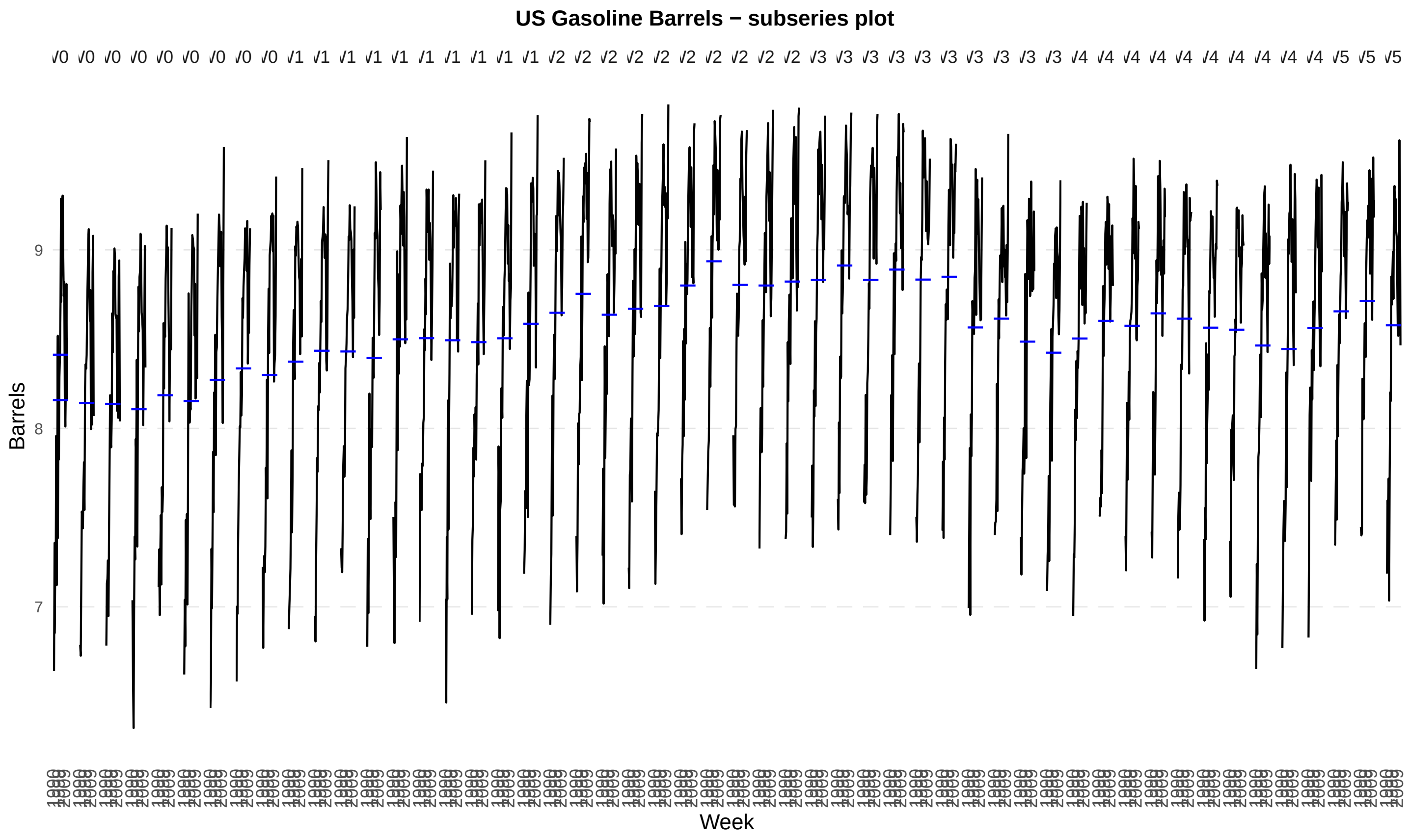

PBS H02 Cost − lag plot
lag 1
lag 2
lag 3
lag 4
lag 5
lag 6
lag 7
lag 8
lag 9
Cost
7e+05
6e+05
5e+05
4e+05
3e+05
2e+05
lag(Cost, n)
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

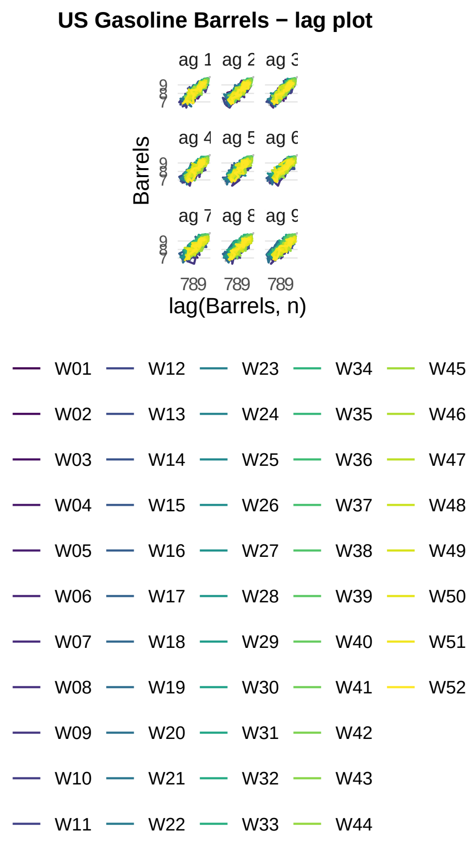


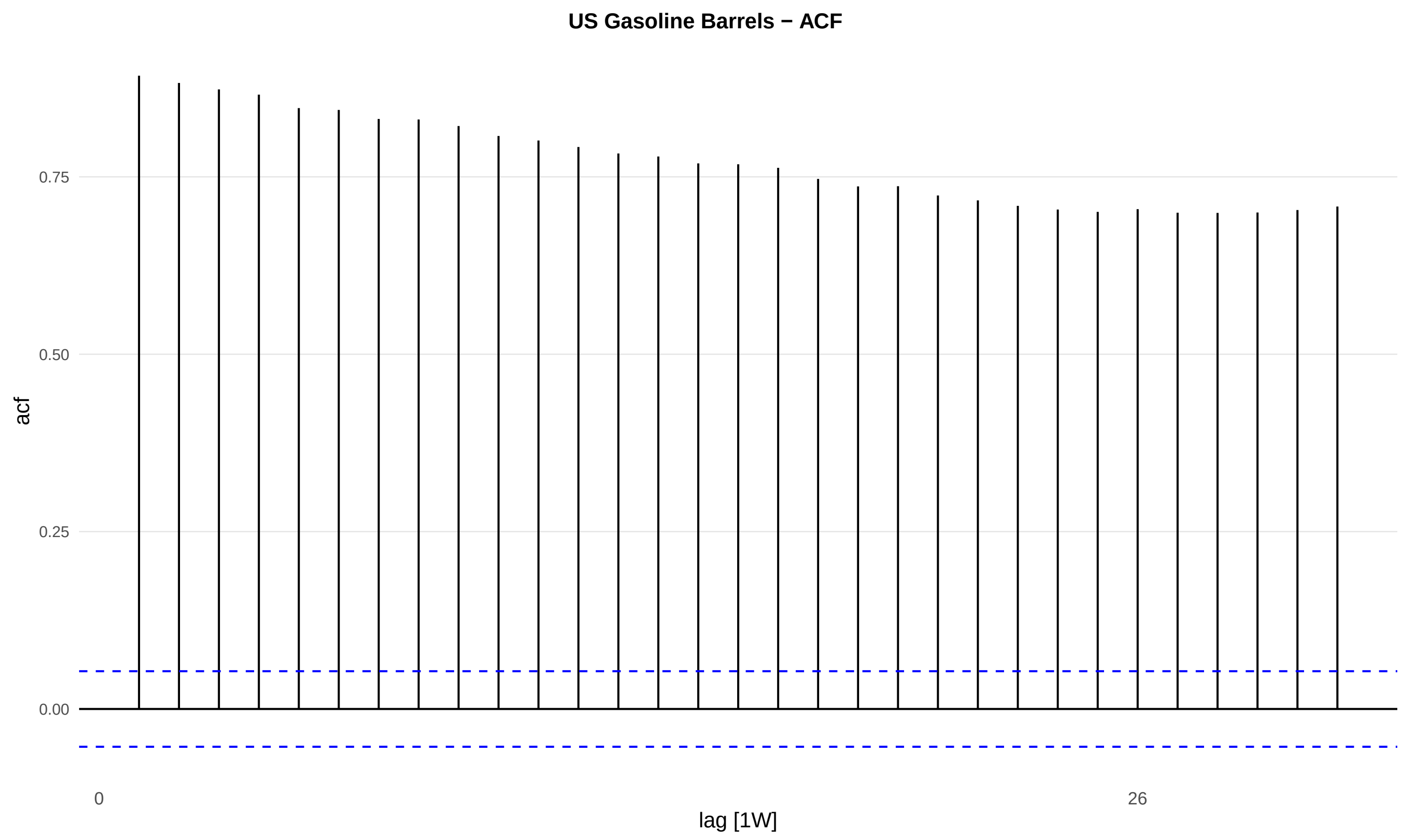
```r
plots_gas <- explore_series(gas_barrels, Barrels, "US Gasoline Barrels")
plots_gas$time; plots_gas$season; plots_gas$subseries; plots_gas$lag; plots_gas$acf
```




US Gasoline Barrels − seasonal plot
Barrels
9
8
7
Jan
Mar
Jun
Oct
Week
1995
2000
2005
2010
2015


US Gasoline Barrels − subseries plot
Barrels
9
8
7
Week





Answer (what we learn): - **US Gasoline Barrels** and **PBS H02 Cost** show clear **seasonality**: repeating within-year patterns and ACF spikes at seasonal lags (and multiples). - **US Employment (Total Private)** shows a strong **trend / nonstationarity**: long-run drift in the time plot and a slowly decaying ACF. - **Hare Pelts** shows **cycles** over multiple years: oscillations in the time plot with an ACF that alternates signs. - **Australian Bricks**

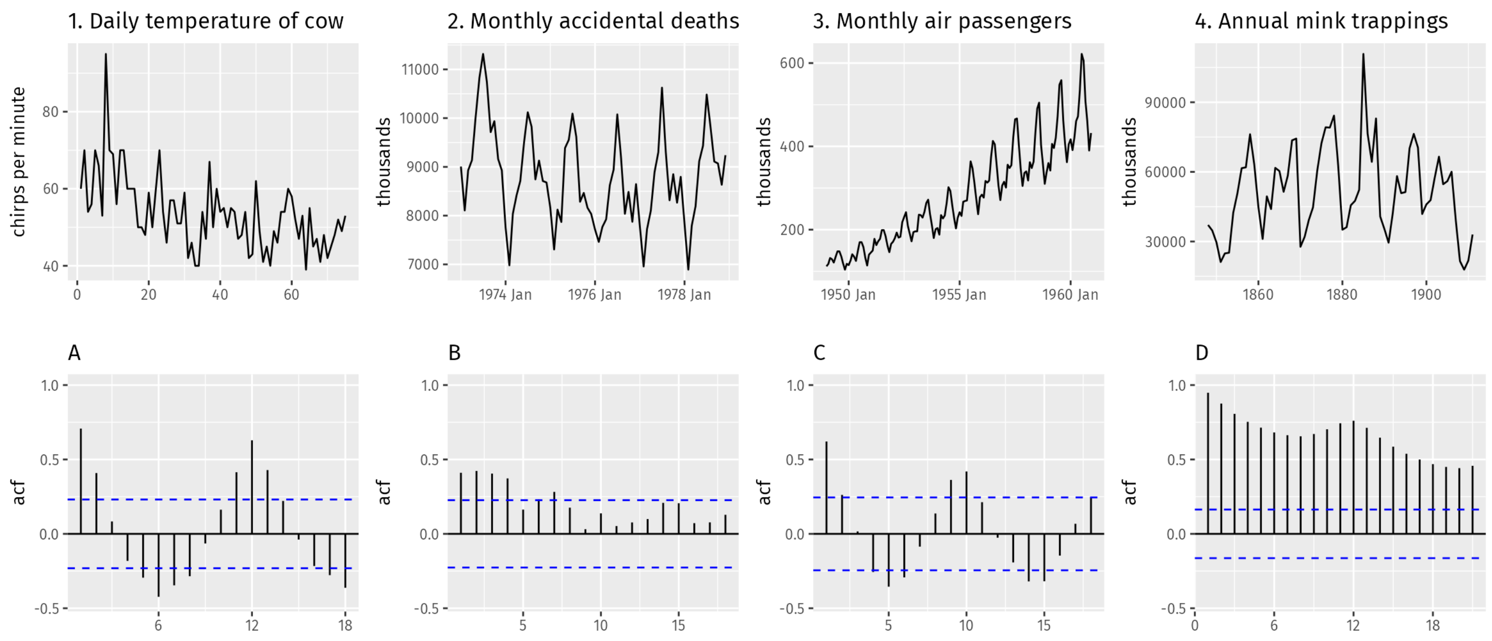
Production shows **unusual years/structural change**: a sharp drop in the early 1980s followed by a sustained lower level and higher volatility from the early 1990s onward.

9 Match time plots to ACF plots

(JUST FOR FUN)

The book's figure is included below for matching.

```r
acf_url <- "https://otexts.com/fpp3/fpp_files/figure-html/acfguess-1.png"
acf_file <- file.path(tempdir(), "acfguess-1.png")

download.file(acf_url, acf_file, mode = "wb")

knitr::include_graphics(acf_file)
```



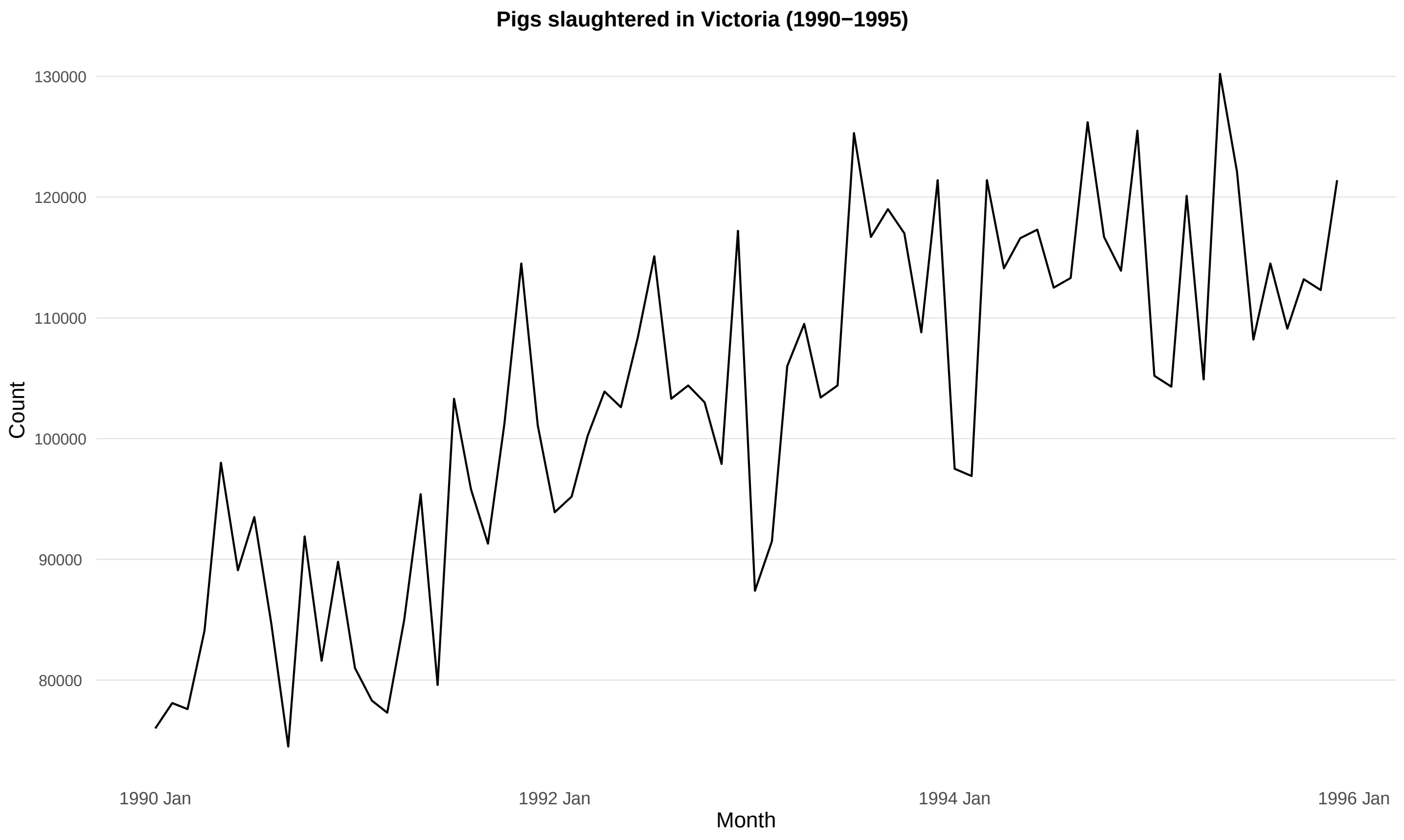
Answer: Based on the figure: - **Time plot A** matches **ACF B** - **Time plot B** matches **ACF A** - **Time plot C** matches **ACF D** - **Time plot D** matches **ACF C**

Justification (brief): - **B □ A:** near-zero, short-memory ACF fits the cow temperature series. - **A □ B:** strong seasonal spikes (esp. lag 12) fit monthly accidental deaths. - **D □ C:** high, slowly decaying ACF fits the trending air passengers series. - **C □ D:** oscillating, alternating-sign ACF fits mink trappings cycles.

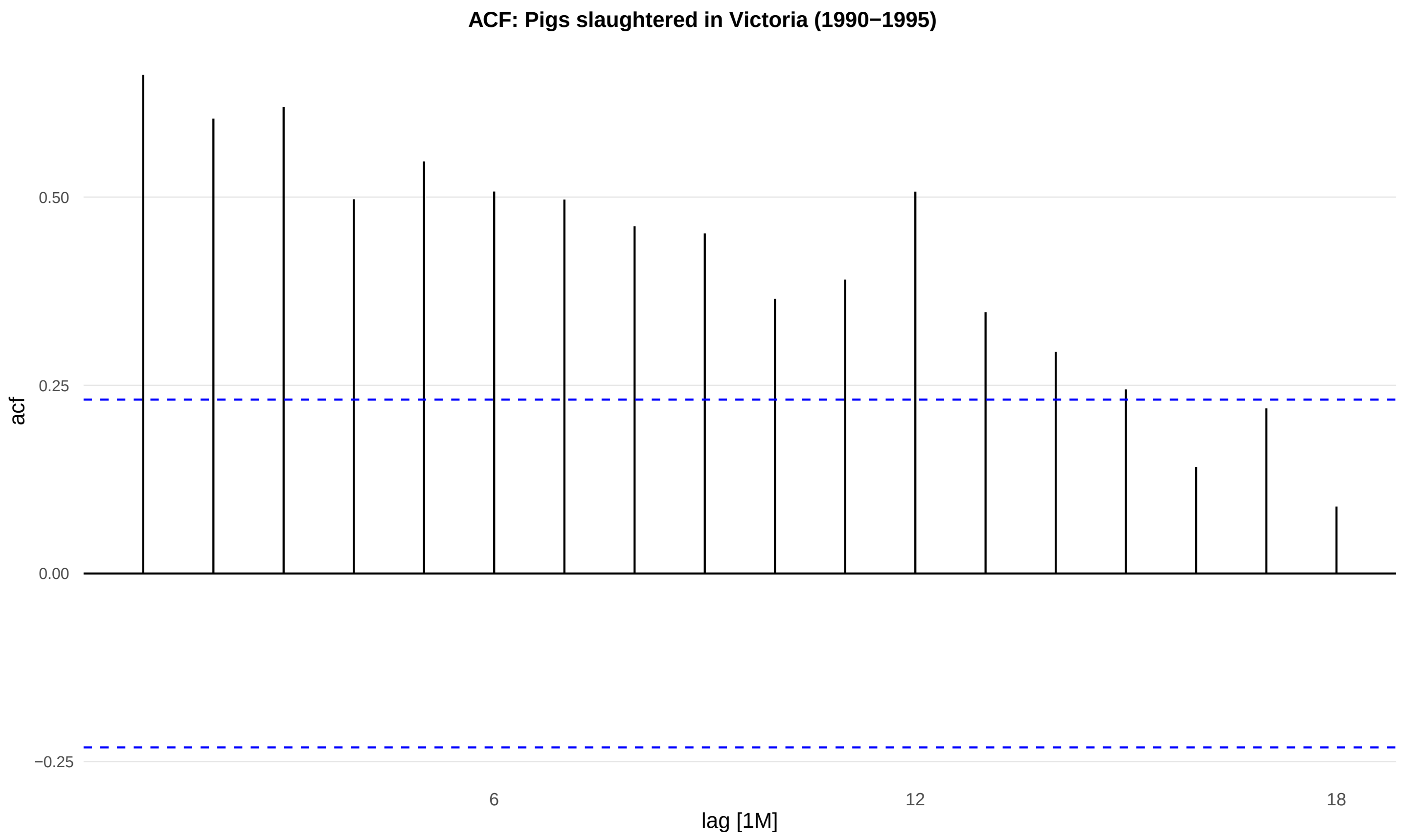
10 aus_livestock pigs in Victoria (1990–1995): autoplot + ACF; compare to white noise

(JUST FOR FUN)

```r
pigs_vic_9095 <- aus_livestock |>
  filter(Animal == "Pigs", State == "Victoria") |>
  filter(year(Month) >= 1990, year(Month) <= 1995)

pigs_vic_9095 |>
  autoplot(Count) +
  labs(title = "Pigs slaughtered in Victoria (1990–1995)", x = "Month", y = "Count")
```

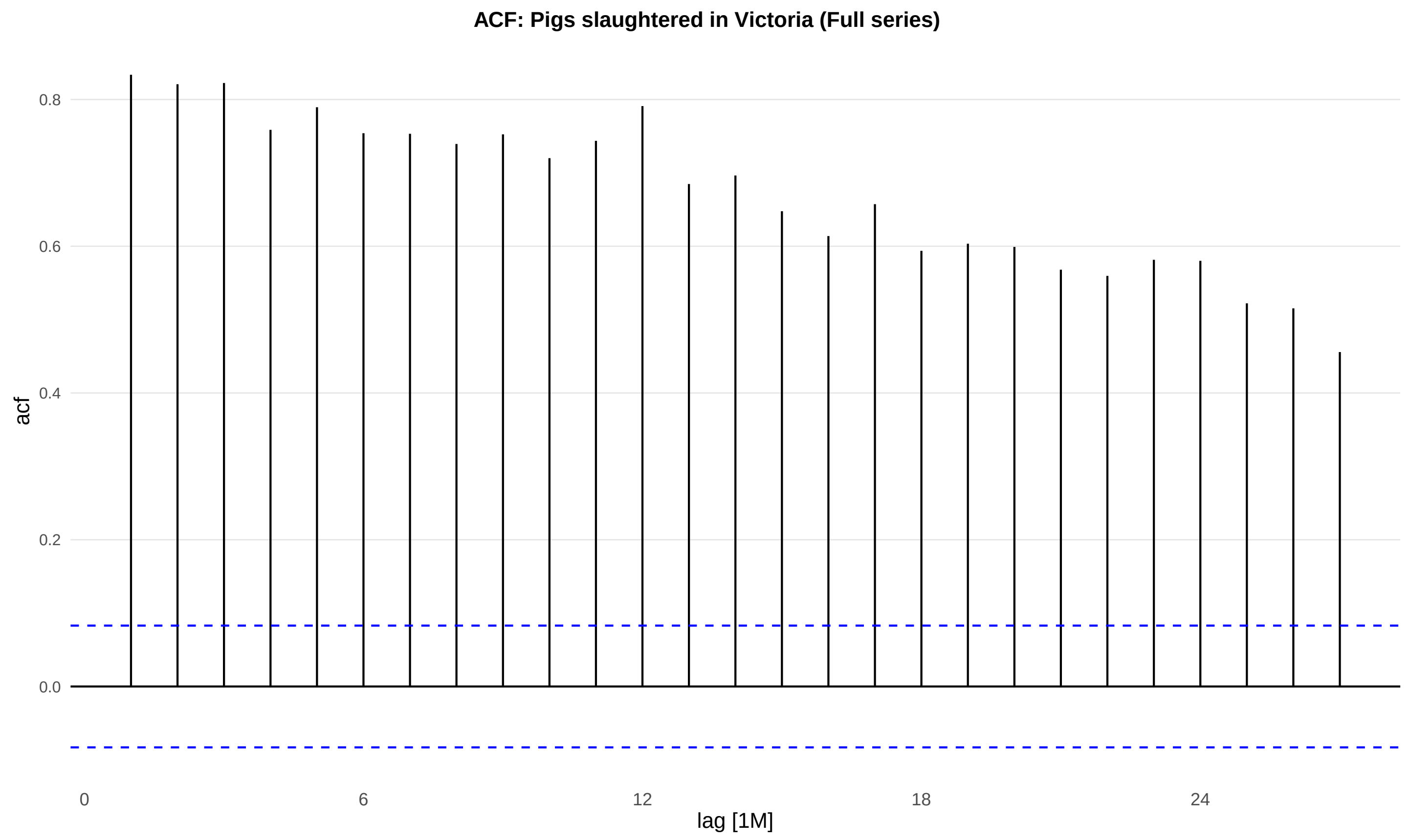


```r
pigs_vic_9095 |>
  ACF(Count) |>
  autoplot() +
  labs(title = "ACF: Pigs slaughtered in Victoria (1990–1995)")
```



Compare to longer period:

```
pigs_vic_full <- aus_livestock |>
  filter(Animal == "Pigs", State == "Victoria")

pigs_vic_full |>
  ACF(Count) |>
  autoplot() +
  labs(title = "ACF: Pigs slaughtered in Victoria (Full series)")
```



Answer:
- Compared with **white noise**, this series shows **structured autocorrelation** (significant ACF spikes rather than hovering near zero), indicating dependence and often seasonality/persistence. - Using a **longer period** typically yields a **more stable ACF estimate** and can make seasonal and low-frequency structure clearer.

11 Google stock daily changes: re-indexing, differences, ACF; assess white noise

(JUST FOR FUN)

Compute daily changes in GOOG closing prices:

```r
dgoog <- gafa_stock |>
  filter(Symbol == "GOOG", year(Date) >= 2018) |>
  mutate(trading_day = row_number()) |>
  update_tsibble(index = trading_day, regular = TRUE) |>
  mutate(diff = difference(Close))

dgoog |> dplyr::glimpse()
```

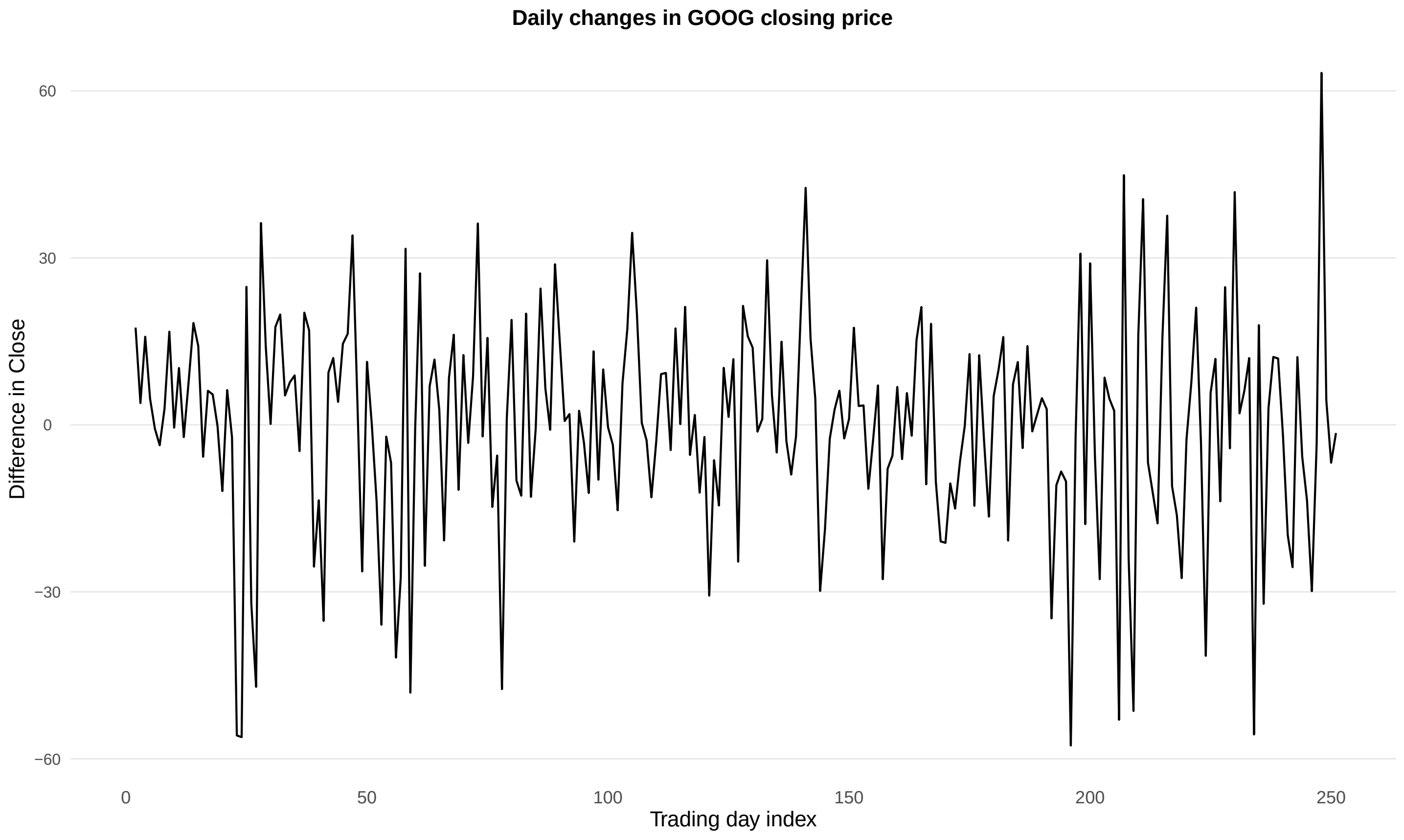
```
## Rows: 251
## Columns: 10
## Key: Symbol [1]
## $ Symbol      <chr> "GOOG", "GOOG", "GOOG", "GOOG", "GOOG", "GOOG", "GOOG", "G~
## $ Date        <date> 2018-01-02, 2018-01-03, 2018-01-04, 2018-01-05, 2018-01-0~
## $ Open        <dbl> 1048.34, 1064.31, 1088.00, 1094.00, 1102.23, 1109.40, 1097~
## $ High        <dbl> 1066.940, 1086.290, 1093.570, 1104.250, 1111.270, 1110.570~
## $ Low         <dbl> 1045.230, 1063.210, 1084.002, 1092.000, 1101.620, 1101.231~
## $ Close       <dbl> 1065.00, 1082.48, 1086.40, 1102.23, 1106.94, 1106.26, 1102~
## $ Adj_Close   <dbl> 1065.00, 1082.48, 1086.40, 1102.23, 1106.94, 1106.26, 1102~
## $ Volume      <dbl> 1237600, 1430200, 1004600, 1279100, 1047600, 902500, 10428~
## $ trading_day <int> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17,~
## $ diff        <dbl> NA, 17.479980, 3.920044, 15.829956, 4.709961, -0.679931, -~
```

11.1 Why re-index the tsibble?

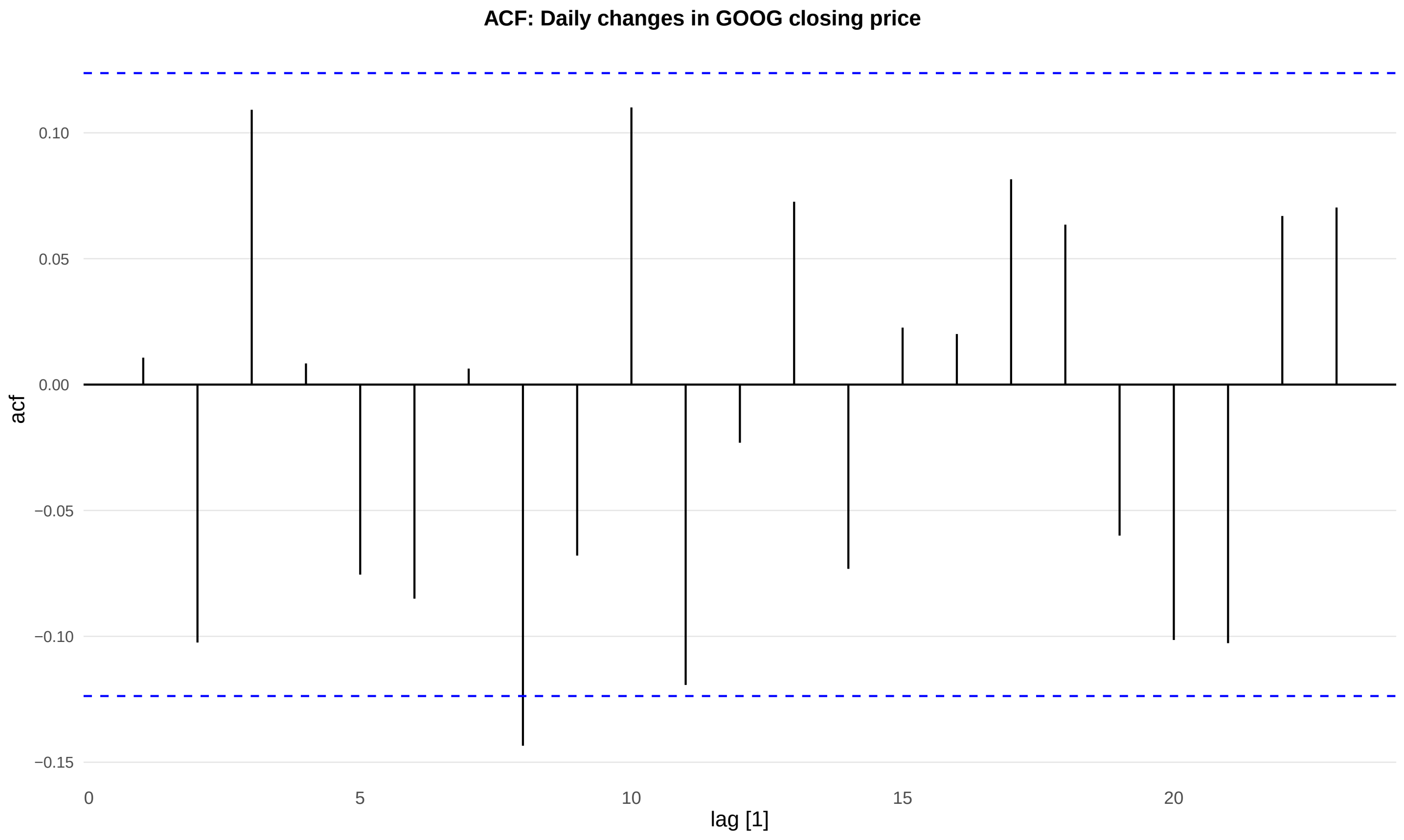
Answer: The `Date` index is not strictly regular because trading does not occur on weekends/holidays. Re-indexing by `trading_day` creates a **regular** index where each step is “next observed trading day,” so lag operations (and the ACF) align with equal steps.

11.2 Plot differences and their ACF

```r
dgoog |>
  autoplot(diff) +
  labs(title = "Daily changes in GOOG closing price", x = "Trading day index", y =
  ↪  "Difference in Close")
```



```
dgoog |>
  ACF(diff) |>
  autoplot() +
  labs(title = "ACF: Daily changes in GOOG closing price")
```



11.3 Do the changes look like white noise?

Answer: Price **changes** often show weak linear autocorrelation (ACF near zero at most lags), consistent with white noise in the mean. However, volatility clustering (periods of larger/smaller variability) can still appear in the time plot, so the series may not be i.i.d. white noise in a strict sense.