Data 624 Homework 1

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Load Packages

```
library(fpp3)
library(USgas)
```

Exercise 1

Explore the following four time series: `Bricks` from `aus_production`, `Lynx` from `pelt`, `Close` from `gafa_stock`, `Demand` from `vic_elec`.

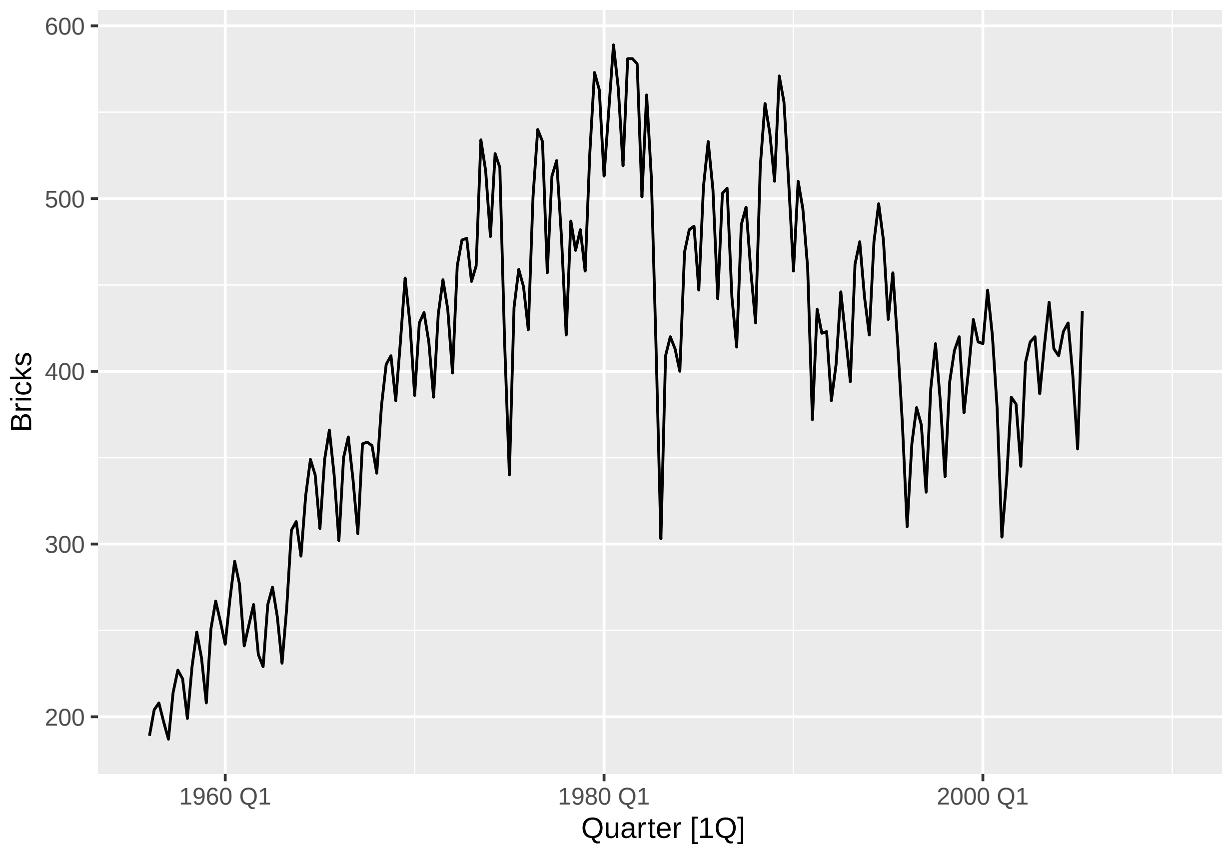
Use `?` (or `help()`) to find out about the data in each series. What is the time interval of each series? Use `autoplot()` to produce a time plot of each series. For the last plot, modify the axis labels and title.

```
?aus_production
aus_production #used to get further familiarized with the data
```

```
## # A tsibble: 218 x 7 [1Q]
##    Quarter  Beer Tobacco Bricks Cement Electricity   Gas
##      <qtr> <dbl>   <dbl>  <dbl>  <dbl>       <dbl> <dbl>
##  1 1956 Q1   284    5225    189    465        3923     5
##  2 1956 Q2   213    5178    204    532        4436     6
##  3 1956 Q3   227    5297    208    561        4806     7
##  4 1956 Q4   308    5681    197    570        4418     6
##  5 1957 Q1   262    5577    187    529        4339     5
##  6 1957 Q2   228    5651    214    604        4811     7
##  7 1957 Q3   236    5317    227    603        5259     7
##  8 1957 Q4   320    6152    222    582        4735     6
##  9 1958 Q1   272    5758    199    554        4608     5
## 10 1958 Q2   233    5641    229    620        5196     7
## # i 208 more rows
```

As can be seen from the results above, the `Bricks` time series from `aus_production` has a quarterly time interval. Below is the time plot illustrating this using `autoplot()`.

```
autoplot(aus_production, Bricks)
```

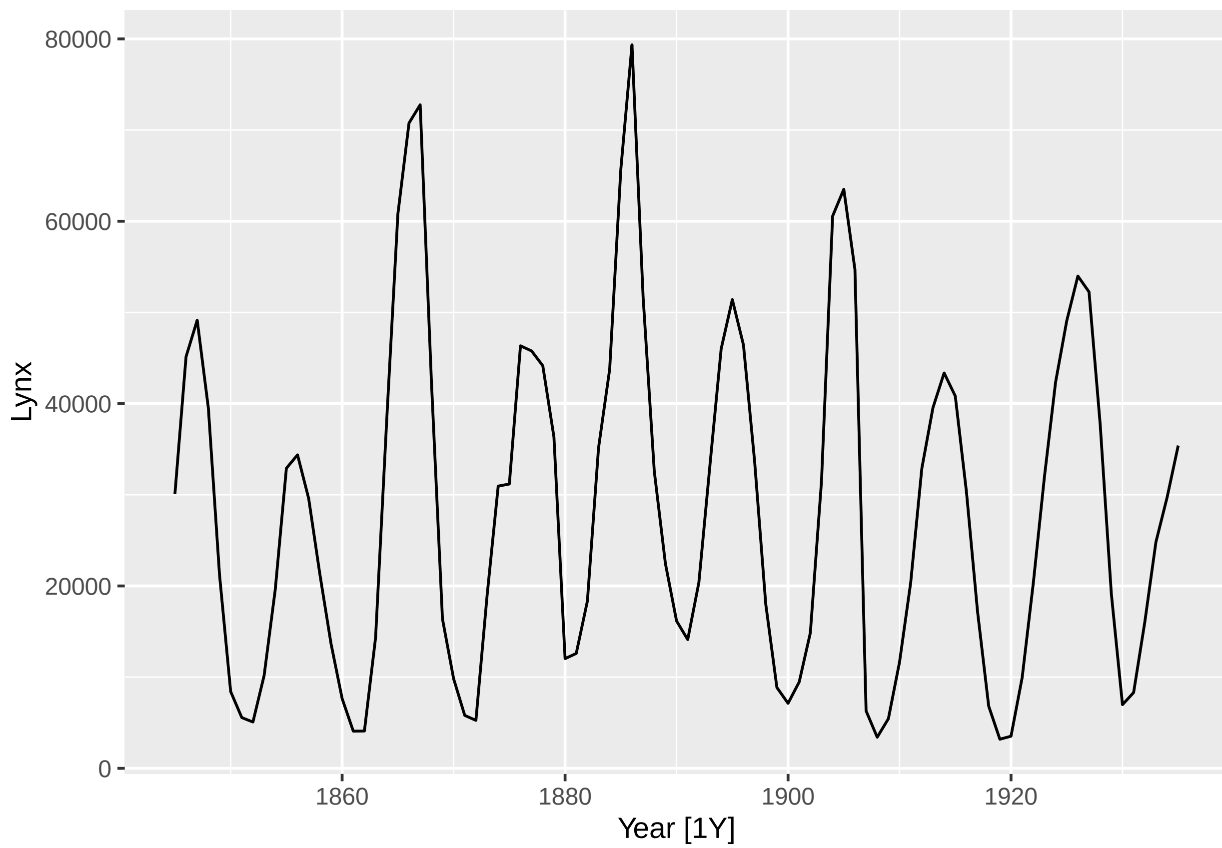



```
?pelt
pelt #used to get further familiarized with the data
```

```
## # A tsibble: 91 x 3 [1Y]
##     Year  Hare  Lynx
##    <dbl> <dbl> <dbl>
##  1  1845 19580 30090
##  2  1846 19600 45150
##  3  1847 19610 49150
##  4  1848 11990 39520
##  5  1849 28040 21230
##  6  1850 58000  8420
##  7  1851 74600  5560
##  8  1852 75090  5080
##  9  1853 88480 10170
## 10  1854 61280 19600
## # i 81 more rows
```

As can be seen from the results above, the `Lynx` time series from `pelt` has an annual time interval. Below is the time plot illustrating this using `autoplot()`.

```
autoplot(pelt, Lynx)
```

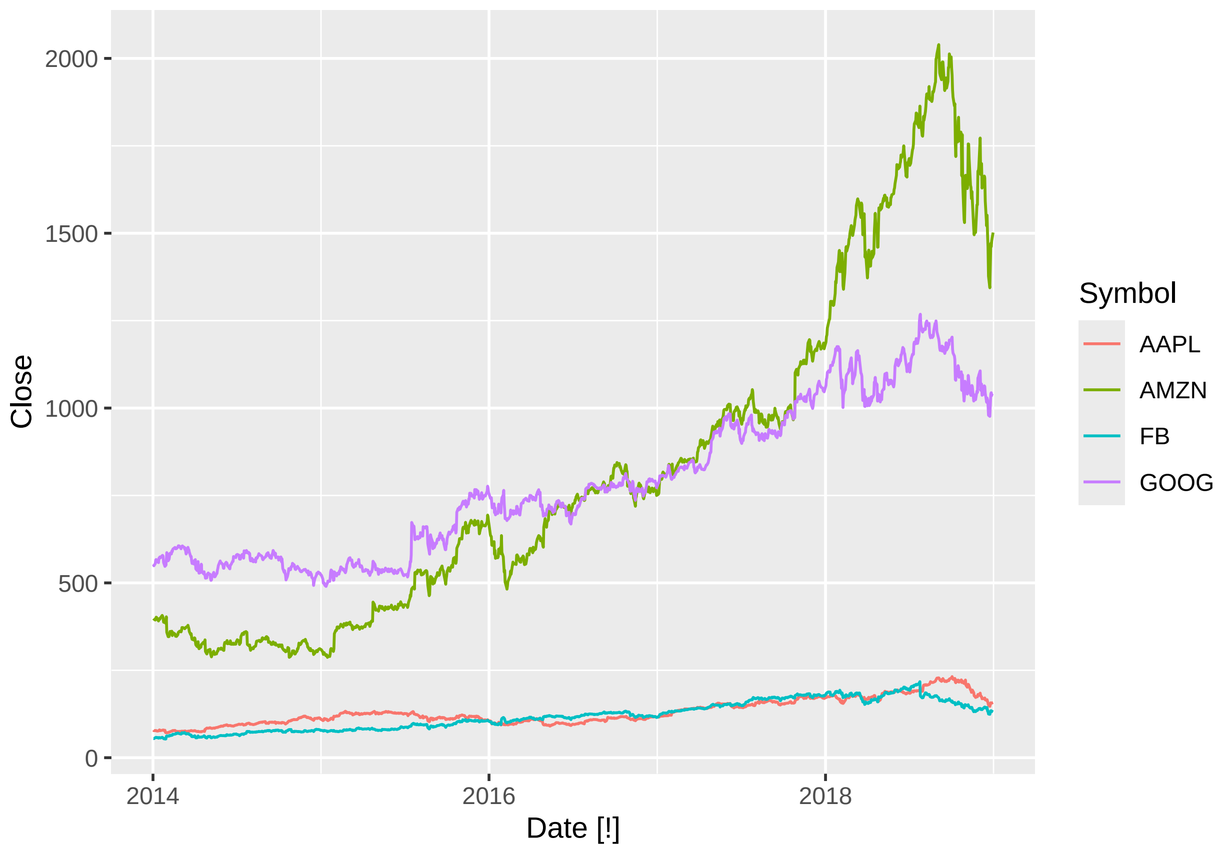



```
?gafa_stock
gafa_stock #used to get further familiarized with the data
```

```
## # A tsibble: 5,032 x 8 [!]
## # Key:       Symbol [4]
##    Symbol Date        Open  High   Low Close Adj_Close    Volume
##    <chr>  <date>     <dbl> <dbl> <dbl> <dbl>     <dbl>     <dbl>
##  1 AAPL   2014-01-02  79.4  79.6  78.9  79.0      67.0  58671200
##  2 AAPL   2014-01-03  79.0  79.1  77.2  77.3      65.5  98116900
##  3 AAPL   2014-01-06  76.8  78.1  76.2  77.7      65.9 103152700
##  4 AAPL   2014-01-07  77.8  78.0  76.8  77.1      65.4  79302300
##  5 AAPL   2014-01-08  77.0  77.9  77.0  77.6      65.8  64632400
##  6 AAPL   2014-01-09  78.1  78.1  76.5  76.6      65.0  69787200
##  7 AAPL   2014-01-10  77.1  77.3  75.9  76.1      64.5  76244000
##  8 AAPL   2014-01-13  75.7  77.5  75.7  76.5      64.9  94623200
##  9 AAPL   2014-01-14  76.9  78.1  76.8  78.1      66.1  83140400
## 10 AAPL   2014-01-15  79.1  80.0  78.8  79.6      67.5  97909700
## # i 5,022 more rows
```

As can be seen from the results above, the `Close` time series from `gafa_stock` has a time interval with specific dates that seem to be business days, which would make sense given that it is a data set on stock prices. Below is the time plot illustrating this using `autoplot()`.

```r
autoplot(gafa_stock, Close)
```

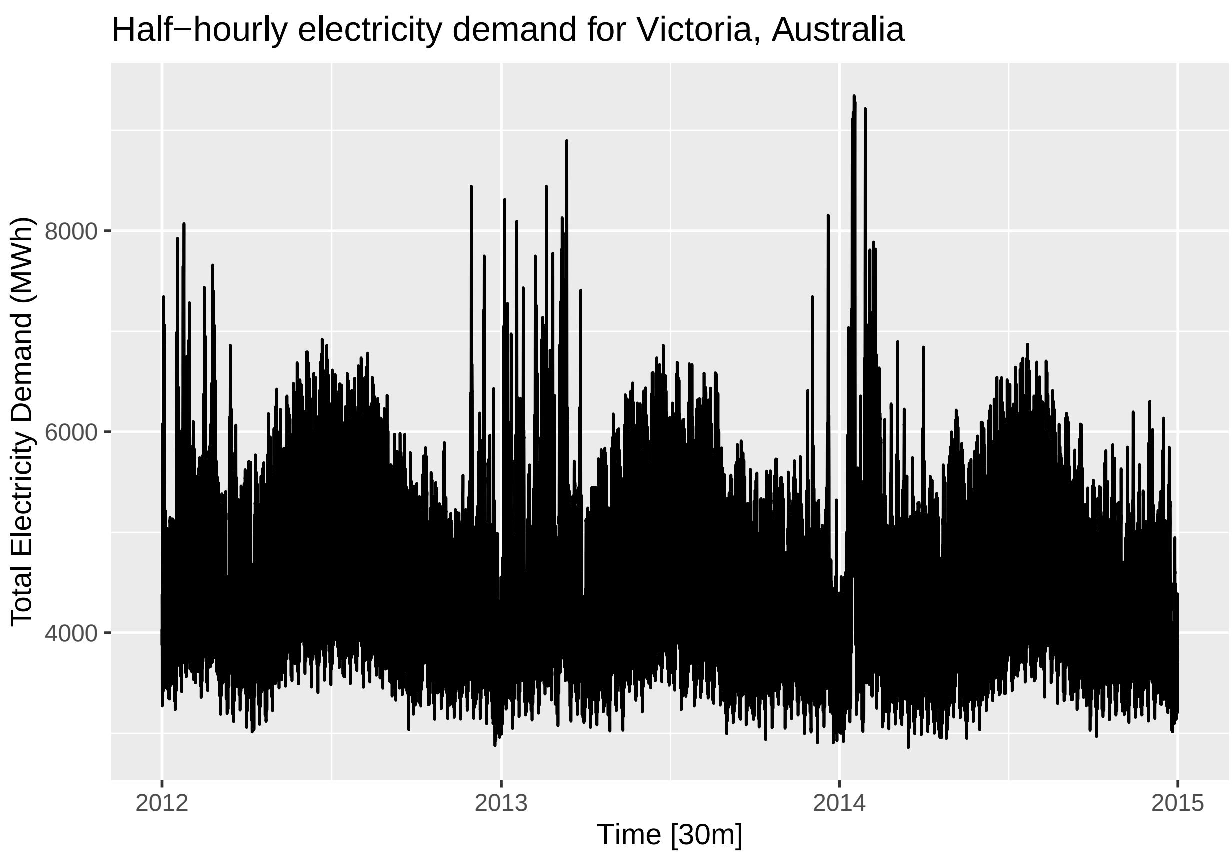



```r
?vic_elec
vic_elec #used to get further familiarized with the data
```

```
## # A tsibble: 52,608 x 5 [30m] <Australia/Melbourne>
##    Time                Demand Temperature Date       Holiday
##    <dttm>               <dbl>       <dbl> <date>     <lgl>
##  1 2012-01-01 00:00:00  4383.        21.4 2012-01-01 TRUE
##  2 2012-01-01 00:30:00  4263.        21.0 2012-01-01 TRUE
##  3 2012-01-01 01:00:00  4049.        20.7 2012-01-01 TRUE
##  4 2012-01-01 01:30:00  3878.        20.6 2012-01-01 TRUE
##  5 2012-01-01 02:00:00  4036.        20.4 2012-01-01 TRUE
##  6 2012-01-01 02:30:00  3866.        20.2 2012-01-01 TRUE
##  7 2012-01-01 03:00:00  3694.        20.1 2012-01-01 TRUE
##  8 2012-01-01 03:30:00  3562.        19.6 2012-01-01 TRUE
##  9 2012-01-01 04:00:00  3433.        19.1 2012-01-01 TRUE
## 10 2012-01-01 04:30:00  3359.        19.0 2012-01-01 TRUE
## # i 52,598 more rows
```

As can be seen from the results above, the `Demand` time series from `vic_elec` has a half-hourly time interval. Below is the time plot illustrating this using `autoplot()` with modified title and axis labels.

```
autoplot(vic_elec, Demand) +
  labs(title = "Half-hourly electricity demand for Victoria, Australia",
       y = "Total Electricity Demand (MWh)")
```



Exercise 2

Use `filter()` to find what days corresponded to the peak closing price for each of the four stocks in `gafa_stock`.

```
aapl_peak <- gafa_stock %>%
  filter(Symbol == "AAPL") %>%
  select(Symbol, Date, Close) %>%
  slice_max(Close, n = 1)
aapl_peak
```

```
## # A tsibble: 1 x 3 [!]
## # Key:       Symbol [1]
##   Symbol Date       Close
##   <chr>  <date>     <dbl>
## 1 AAPL   2018-10-03  232.
```

```
amzn_peak <- gafa_stock %>%
  filter(Symbol == "AMZN") %>%
```

```r
  select(Symbol, Date, Close) %>%
  slice_max(Close, n = 1)
amzn_peak
```

```
## # A tsibble: 1 x 3 [!]
## # Key:       Symbol [1]
##   Symbol Date       Close
##   <chr>  <date>     <dbl>
## 1 AMZN   2018-09-04 2040.
```

```r
fb_peak <- gafa_stock %>%
  filter(Symbol == "FB") %>%
  select(Symbol, Date, Close) %>%
  slice_max(Close, n = 1)
fb_peak
```

```
## # A tsibble: 1 x 3 [!]
## # Key:       Symbol [1]
##   Symbol Date       Close
##   <chr>  <date>     <dbl>
## 1 FB     2018-07-25  218.
```

```r
goog_peak <- gafa_stock %>%
  filter(Symbol == "GOOG") %>%
  select(Symbol, Date, Close) %>%
  slice_max(Close, n = 1)
goog_peak
```

```
## # A tsibble: 1 x 3 [!]
## # Key:       Symbol [1]
##   Symbol Date       Close
##   <chr>  <date>     <dbl>
## 1 GOOG   2018-07-26 1268.
```

Exercise 3

Download the file `tute1.csv` from the book website, open it in Excel (or some other spreadsheet application), and review its contents. You should find four columns of information. Columns B through D each contain a quarterly series, labelled Sales, AdBudget and GDP. Sales contains the quarterly sales for a small company over the period 1981-2005. AdBudget is the advertising budget and GDP is the gross domestic product. All series have been adjusted for inflation.

You can read the data into R with the following script: `tute1 <- readr::read_csv("tute1.csv") View(tute1)`

Convert the data to time series `mytimeseries <- tute1 |>   mutate(Quarter = yearquarter(Quarter)) |>   as_tsibble(index = Quarter)`

Construct time series plots of each of the three series `mytimeseries |>   pivot_longer(-Quarter) |> ggplot(aes(x = Quarter, y = value, colour = name)) +   geom_line() +   facet_grid(name ~ ., scales = "free_y")` Check what happens when you don't include `facet_grid()`.

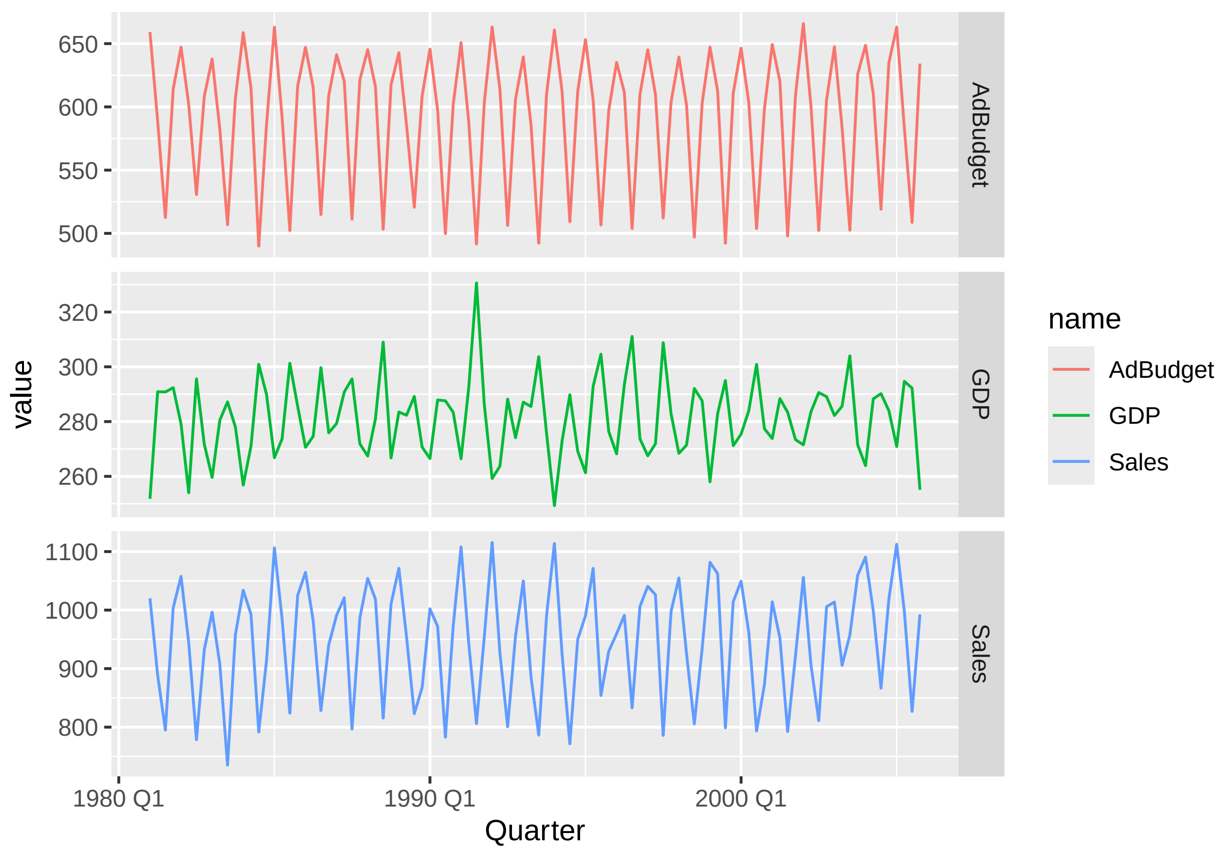
```r
url <- "https://raw.githubusercontent.com/Stevee-G/Data624/refs/heads/main/tute1.csv"
tute1 <- readr::read_csv(url) #Had to modify the command in order to make the RMD reproducible
```

```
## Rows: 100 Columns: 4
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## dbl  (3): Sales, AdBudget, GDP
## date (1): Quarter
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

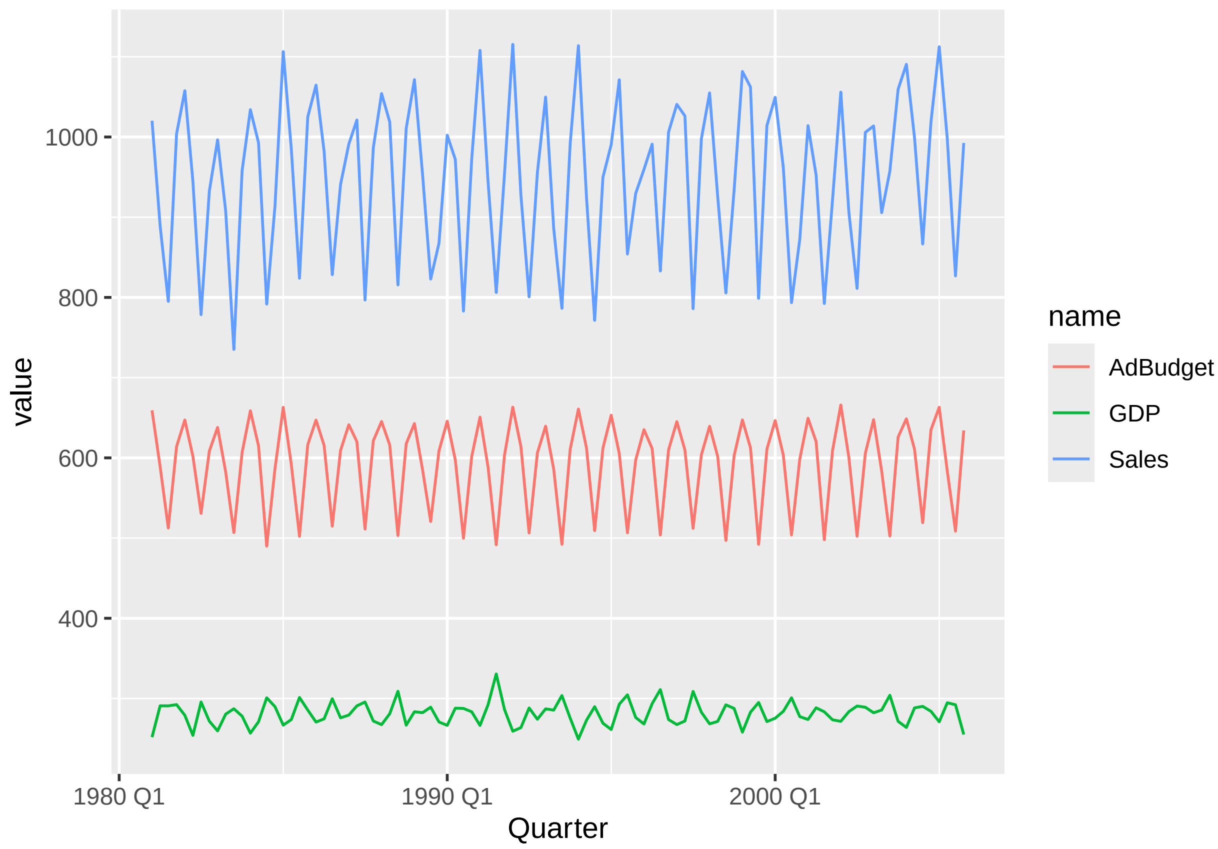
```r
View(tute1)

mytimeseries <- tute1 %>%
  mutate(Quarter = yearquarter(Quarter)) %>%
  as_tsibble(index = Quarter) #Modified the pipe due to personal preference

mytimeseries %>%
  pivot_longer(-Quarter) %>%
  ggplot(aes(x = Quarter, y = value, colour = name)) +
  geom_line() +
  facet_grid(name ~ ., scales = "free_y")
```



```r
mytimeseries %>%
  pivot_longer(-Quarter) %>%
  ggplot(aes(x = Quarter, y = value, colour = name)) +
  geom_line()
```



Exercise 4

The `USgas` package contains data on the demand for natural gas in the US.

Install the `USgas` package. Create a `tsibble` from `us_total` with year as the index and state as the key. Plot the annual natural gas consumption by state for the New England area (comprising the states of Maine, Vermont, New Hampshire, Massachusetts, Connecticut and Rhode Island).

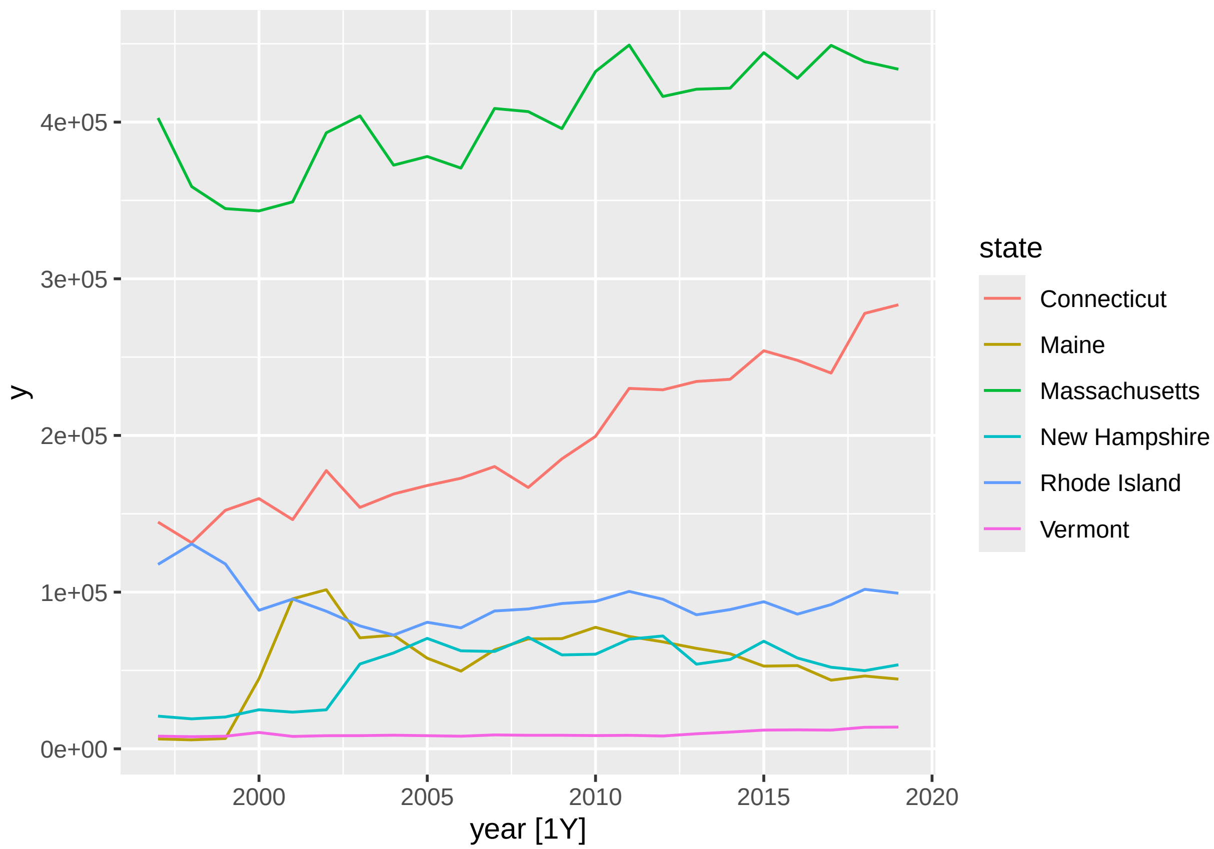
```r
#USgas package was installed and loaded in a previous section
?us_total
glimpse(us_total)
```

```
## Rows: 1,266
## Columns: 3
## $ year  <int> 1997, 1998, 1999, 2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007~
## $ state <chr> "Alabama", "Alabama", "Alabama", "Alabama", "Alabama", "Alabama"~
## $ y     <int> 324158, 329134, 337270, 353614, 332693, 379343, 350345, 382367, ~
```

```r
us_total_ts <- us_total %>%
  as_tsibble(index = year, key = state)

new_england <- us_total_ts %>%
  filter(state == "Maine" |
           state == "Vermont" |
           state == "New Hampshire" |
           state == "Massachusetts" |
           state == "Connecticut" |
           state == "Rhode Island")

autoplot(new_england, y)
```



Exercise 5

Download `tourism.xlsx` from the book website and read it into R using `readxl::read_excel()`. Create a tsibble which is identical to the `tourism` tsibble from the `tsibble` package. Find what combination of `Region` and `Purpose` had the maximum number of overnight trips on average. Create a new tsibble which combines the Purposes and Regions, and just has total trips by State.

```r
url1 <- "https://raw.githubusercontent.com/Stevee-G/Data624/refs/heads/main/tourism.csv"
tourism1 <- readr::read_csv(url1) #Had to resort to csv due to an issue with OneDrive making the excel
glimpse(tourism1)
```

```
## Rows: 24,320
## Columns: 5
## $ Quarter <date> 1998-01-01, 1998-04-01, 1998-07-01, 1998-10-01, 1999-01-01, 1~
## $ 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~
```

```r
tourism #Take a look at the tourism tsibble in order to compare with tsibble made from the tourism exce
```

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:       Region, State, Purpose [304]
##    Quarter Region   State           Purpose  Trips
##      <qtr> <chr>    <chr>           <chr>    <dbl>
##  1 1998 Q1 Adelaide South Australia Business  135.
##  2 1998 Q2 Adelaide South Australia Business  110.
##  3 1998 Q3 Adelaide South Australia Business  166.
##  4 1998 Q4 Adelaide South Australia Business  127.
##  5 1999 Q1 Adelaide South Australia Business  137.
##  6 1999 Q2 Adelaide South Australia Business  200.
##  7 1999 Q3 Adelaide South Australia Business  169.
##  8 1999 Q4 Adelaide South Australia Business  134.
##  9 2000 Q1 Adelaide South Australia Business  154.
## 10 2000 Q2 Adelaide South Australia Business  169.
## # i 24,310 more rows
```

```r
?tourism #Get familiar with tourism tsibble to identify index

tourism1_ts <- tourism1 %>%
  mutate(Quarter = yearquarter(Quarter)) %>%
  as_tsibble(index = Quarter, key = c(Region, State, Purpose))
tourism1_ts #Glimpse and compare tourism1_ts to tourism tsibble
```

```
## # A tsibble: 24,320 x 5 [1Q]
## # Key:       Region, State, Purpose [304]
##    Quarter Region   State           Purpose  Trips
##      <qtr> <chr>    <chr>           <chr>    <dbl>
##  1 1998 Q1 Adelaide South Australia Business  135.
##  2 1998 Q2 Adelaide South Australia Business  110.
##  3 1998 Q3 Adelaide South Australia Business  166.
##  4 1998 Q4 Adelaide South Australia Business  127.
##  5 1999 Q1 Adelaide South Australia Business  137.
##  6 1999 Q2 Adelaide South Australia Business  200.
##  7 1999 Q3 Adelaide South Australia Business  169.
##  8 1999 Q4 Adelaide South Australia Business  134.
##  9 2000 Q1 Adelaide South Australia Business  154.
## 10 2000 Q2 Adelaide South Australia Business  169.
## # i 24,310 more rows
```

By comparing the tsibbles produced above we can say for certain that the new `tourism1_ts` is identical to the original `tourism`.

```r
max_avg_trips <- tourism1_ts %>%
  group_by(Region, Purpose) %>%
  summarise(avg_trips = mean(Trips)) %>%
  slice_max(avg_trips, n = 1) %>%
  arrange(desc(avg_trips))
max_avg_trips
```

```
## # A tsibble: 76 x 4 [1Q]
## # Key:       Region, Purpose [76]
## # Groups:    Region [76]
##    Region                 Purpose  Quarter avg_trips
##    <chr>                  <chr>      <qtr>     <dbl>
##  1 Melbourne              Visiting 2017 Q4      985.
##  2 Sydney                 Business 2001 Q4      948.
##  3 South Coast            Holiday  1998 Q1      915.
##  4 North Coast NSW        Holiday  2016 Q1      906.
##  5 Brisbane               Visiting 2016 Q4      796.
##  6 Gold Coast             Holiday  2002 Q1      711.
##  7 Sunshine Coast         Holiday  2005 Q1      617.
##  8 Australia's South West Holiday  2016 Q1      612.
##  9 Great Ocean Road       Holiday  1998 Q1      548.
## 10 Experience Perth       Visiting 2016 Q1      538.
## # i 66 more rows
```

Through the code chunk above, we can see that the combination of `Region` and `Purpose` with the maximum number of overnight trips on average was "Melbourne" and "Visiting".

```r
total_trips <- tourism1_ts %>%
  group_by(State) %>% #By using the group_by function on State, we can collapse all region and purpose
  summarise(tot_trips = sum(Trips))
total_trips
```

```
## # A tsibble: 640 x 3 [1Q]
## # Key:       State [8]
##    State Quarter tot_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
```

Exercise 8

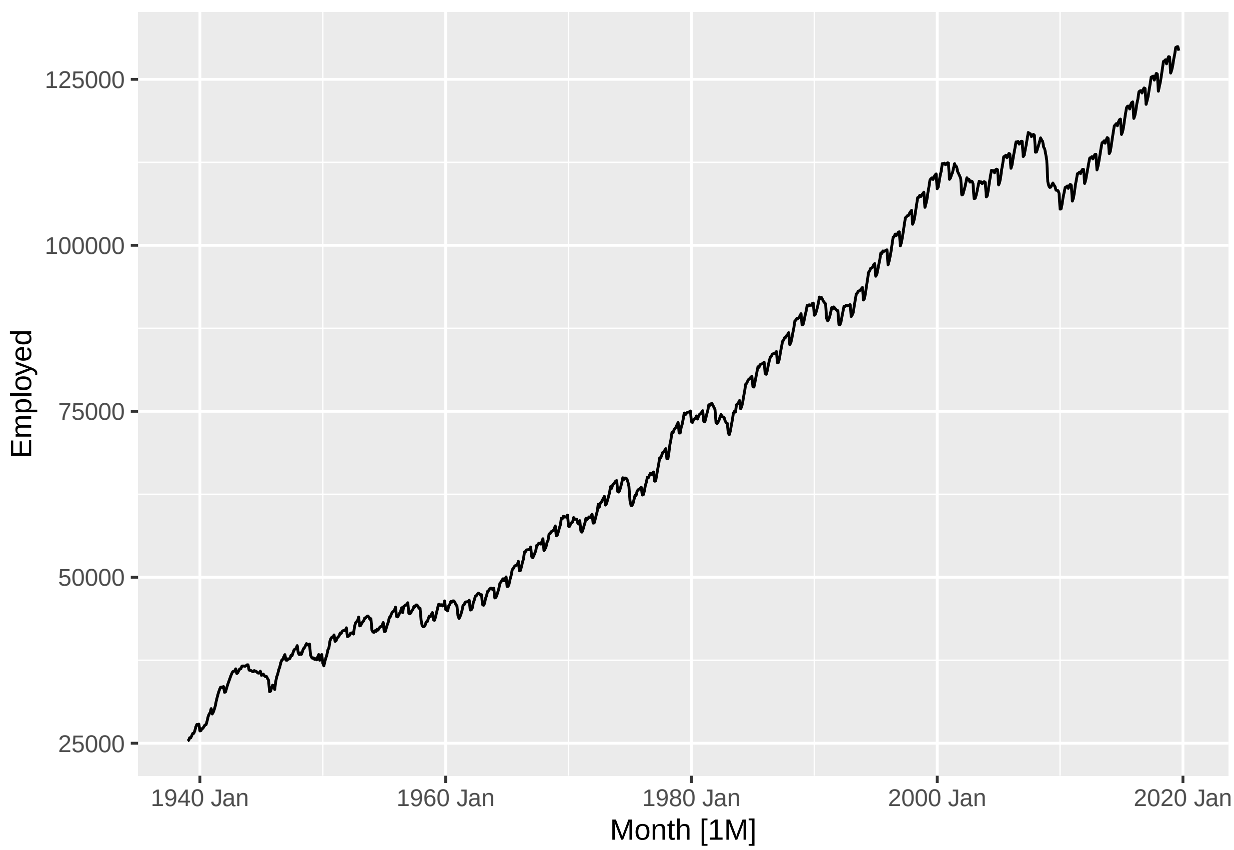
Use the following graphics functions: `autoplot()`, `gg_season()`, `gg_subseries()`, `gg_lag()`, `ACF()` and explore features from the following time series: "Total Private" `Employed` from `us_employment`, `Bricks` from `aus_production`, `Hare` from `pelt`, "H02" `Cost` from `PBS`, and `Barrels` from `us_gasoline`.

Can you spot any seasonality, cyclicity and trend? What do you learn about the series? What can you say about the seasonal patterns? Can you identify any unusual years?

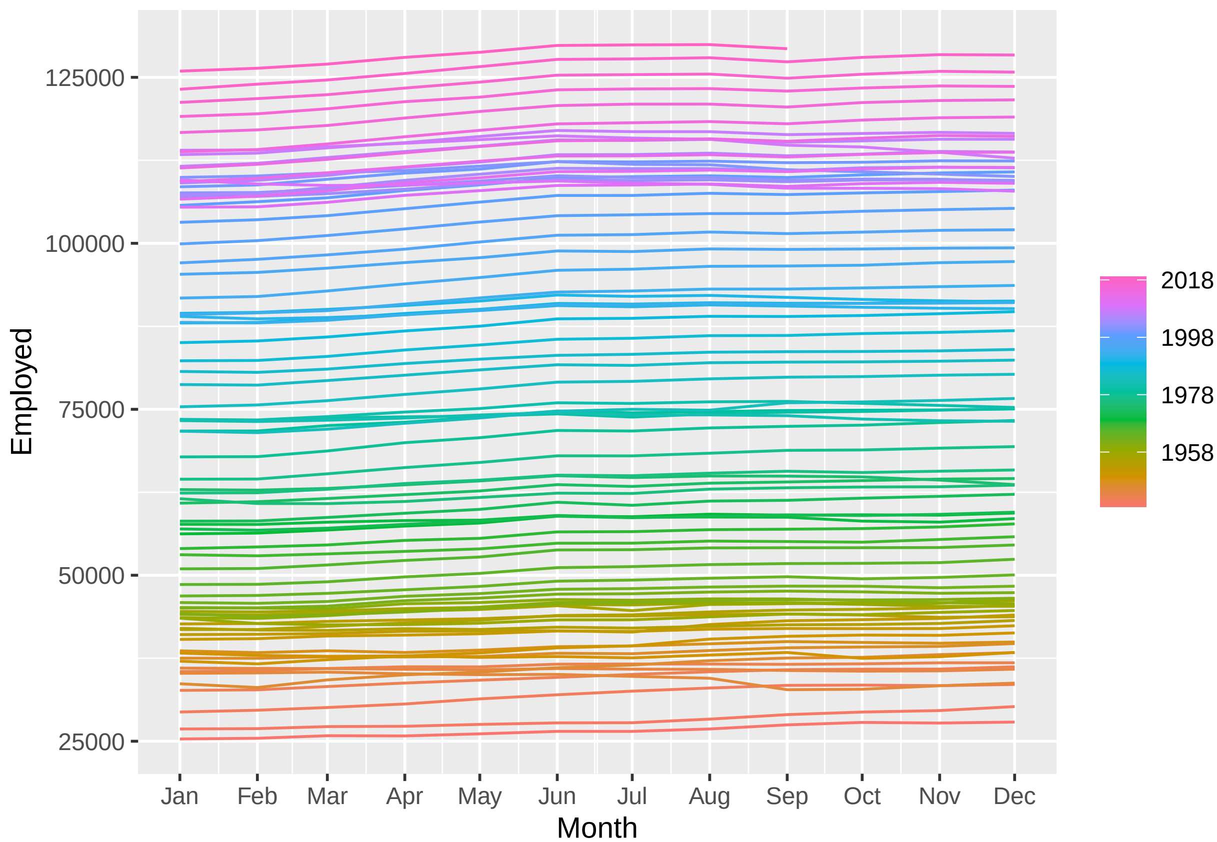
```
us_employment
```

```
## # A tsibble: 143,412 x 4 [1M]
## # Key:       Series_ID [148]
##       Month Series_ID     Title         Employed
##       <mth> <chr>         <chr>            <dbl>
##  1 1939 Jan CEU0500000001 Total Private    25338
##  2 1939 Feb CEU0500000001 Total Private    25447
##  3 1939 Mar CEU0500000001 Total Private    25833
##  4 1939 Apr CEU0500000001 Total Private    25801
##  5 1939 May CEU0500000001 Total Private    26113
##  6 1939 Jun CEU0500000001 Total Private    26485
##  7 1939 Jul CEU0500000001 Total Private    26481
##  8 1939 Aug CEU0500000001 Total Private    26848
##  9 1939 Sep CEU0500000001 Total Private    27468
## 10 1939 Oct CEU0500000001 Total Private    27830
## # i 143,402 more rows
```

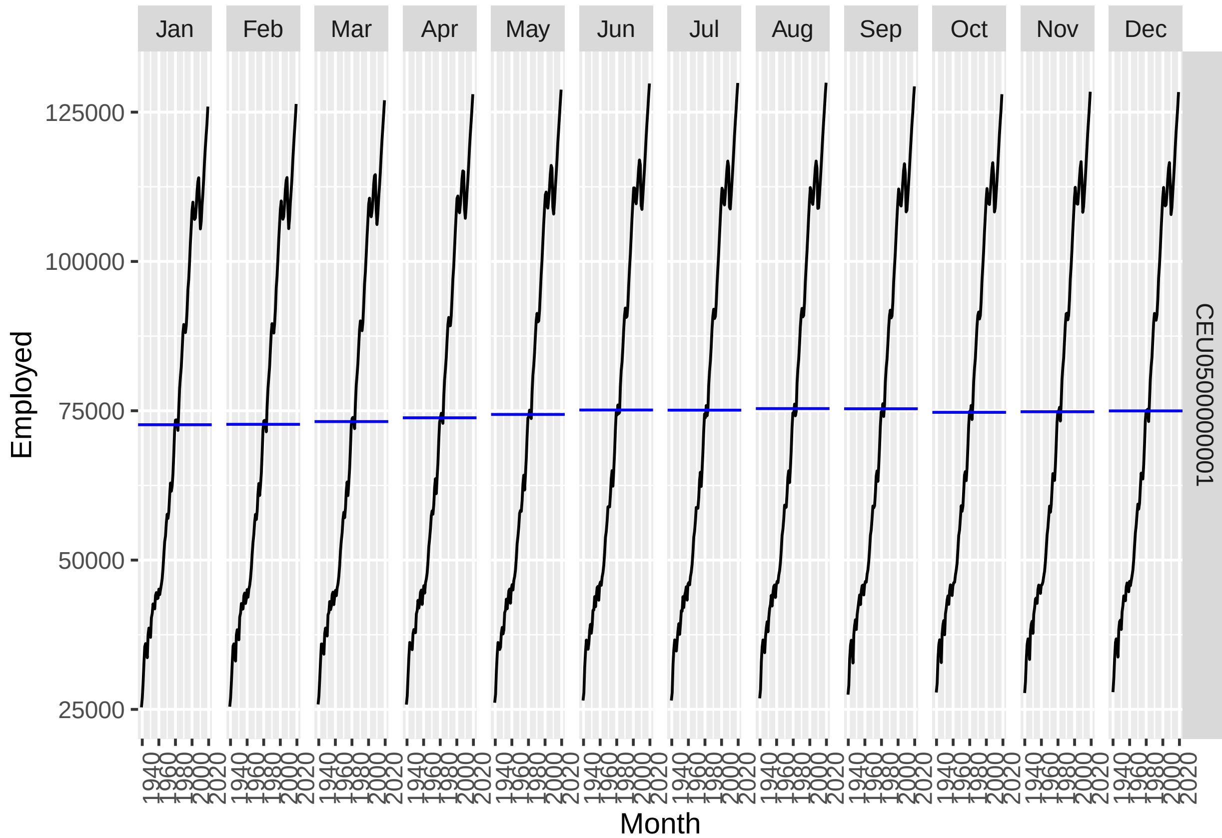
```
private_employment <- us_employment %>%
  filter(Title == "Total Private")
autoplot(private_employment, Employed)
```



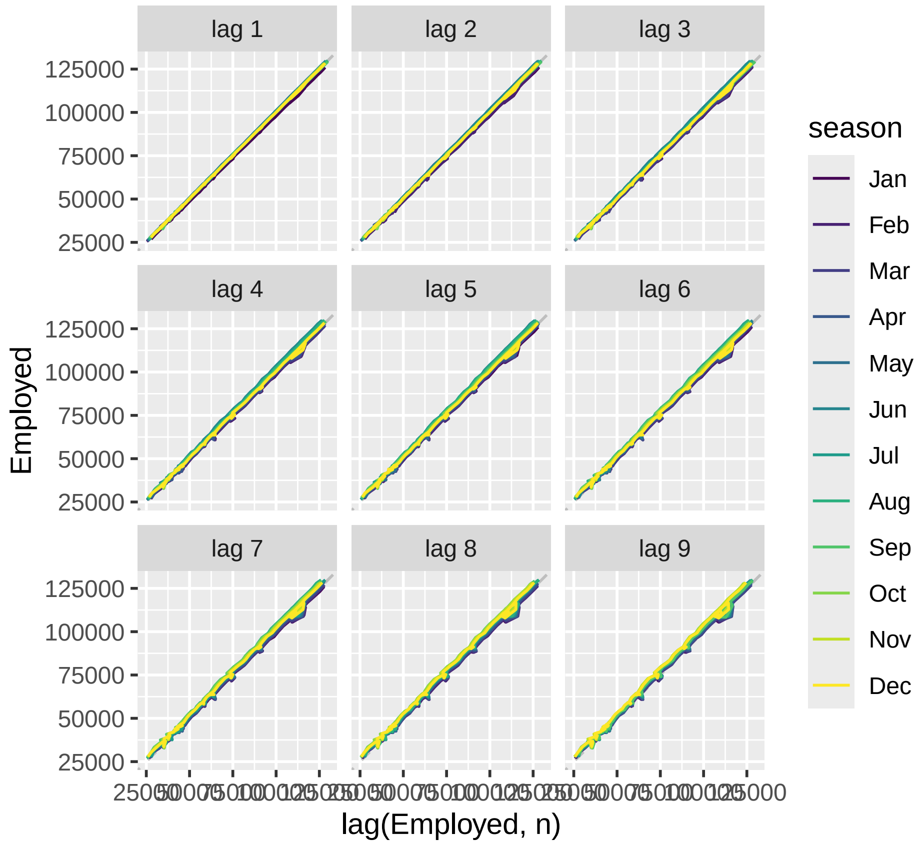
```r
gg_season(private_employment, y = Employed)
```



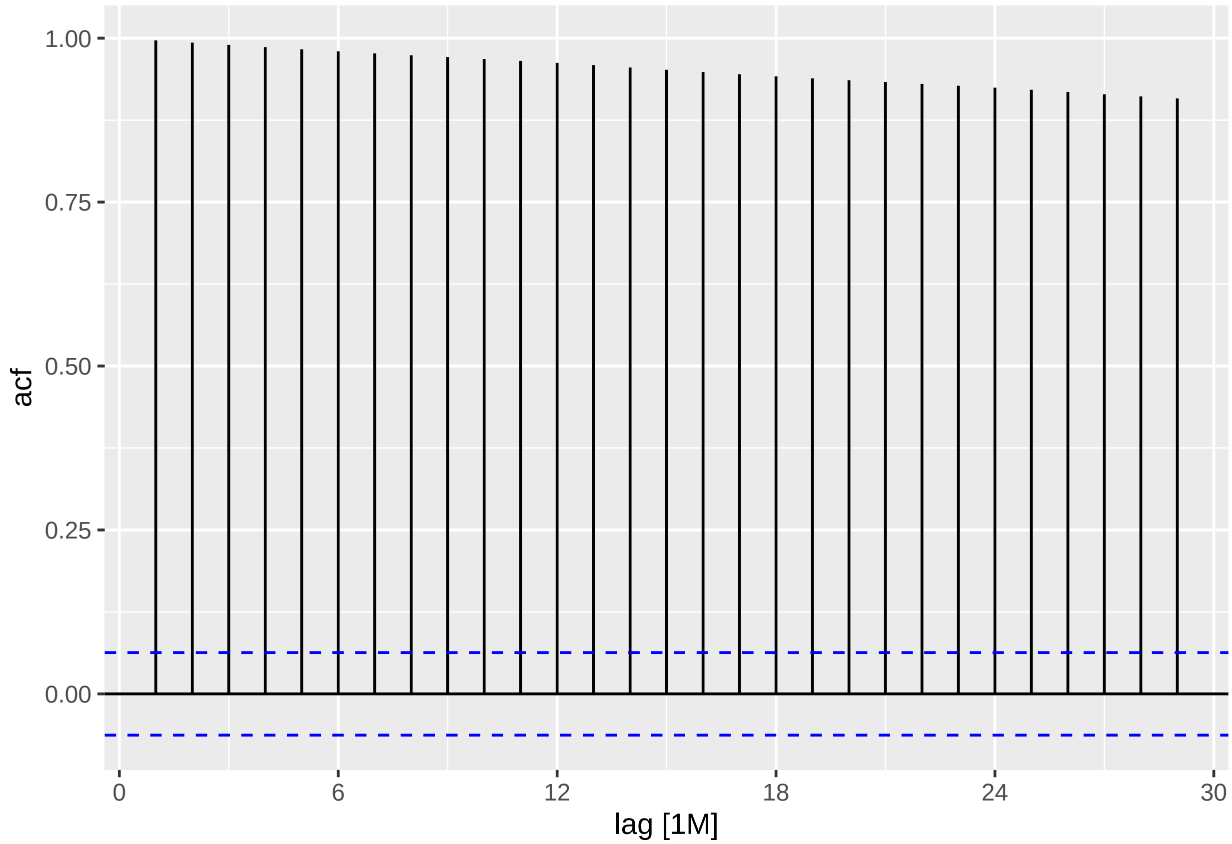

```r
gg_subseries(private_employment, y = Employed)
```




```
gg_lag(private_employment, y = Employed)
```




```
ACF(private_employment, y = Employed) %>%
  autoplot()
```

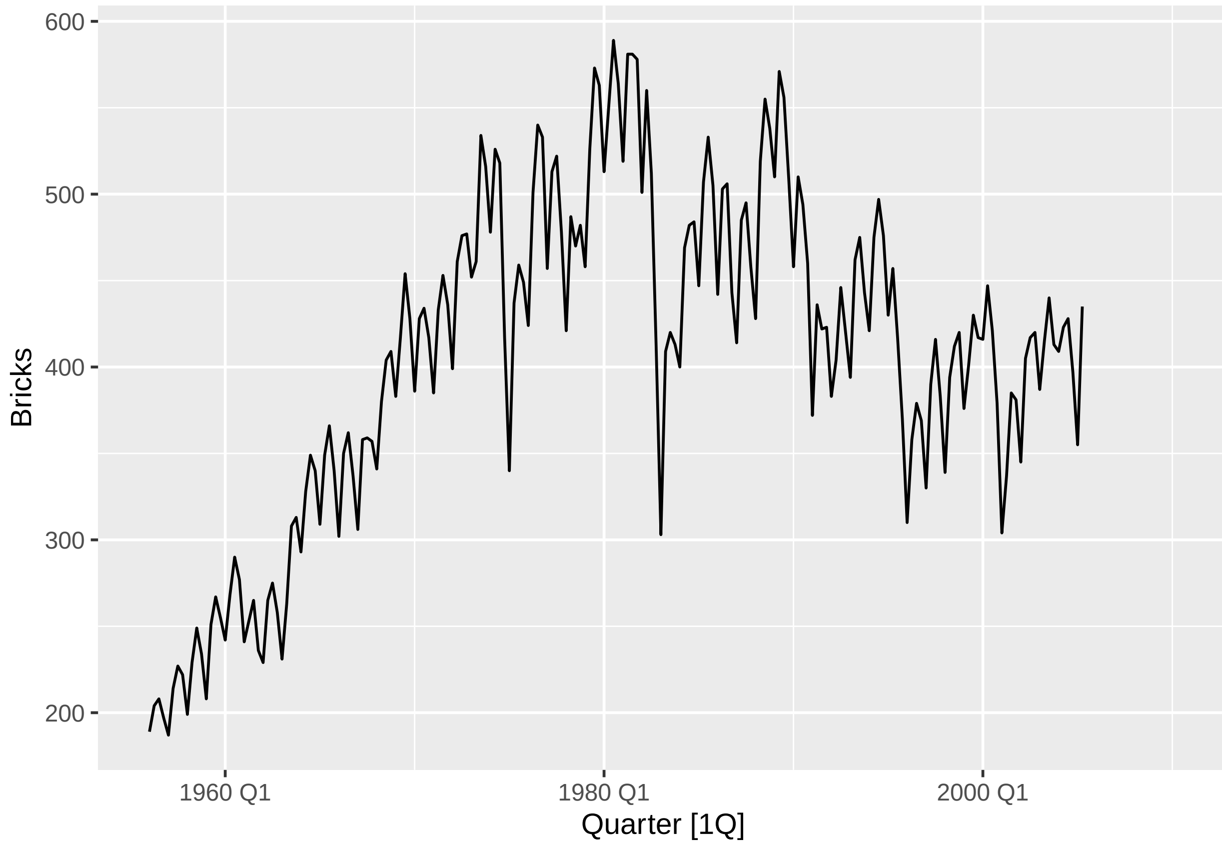


As can be seen above, the "Total Private" `Employed` time series from `us_employment` does seem to show some seasonality where the numbers employed go up through the middle months of the year just to drop again towards the end of the year but still higher than they were in the beginning of the year. The series did have some cyclicity throughout the 80 year stretch that could be due to fluctuations in the economy, especially the unusual dip recorded in the few years leading up to 2010. The over all trend of the series is positive.

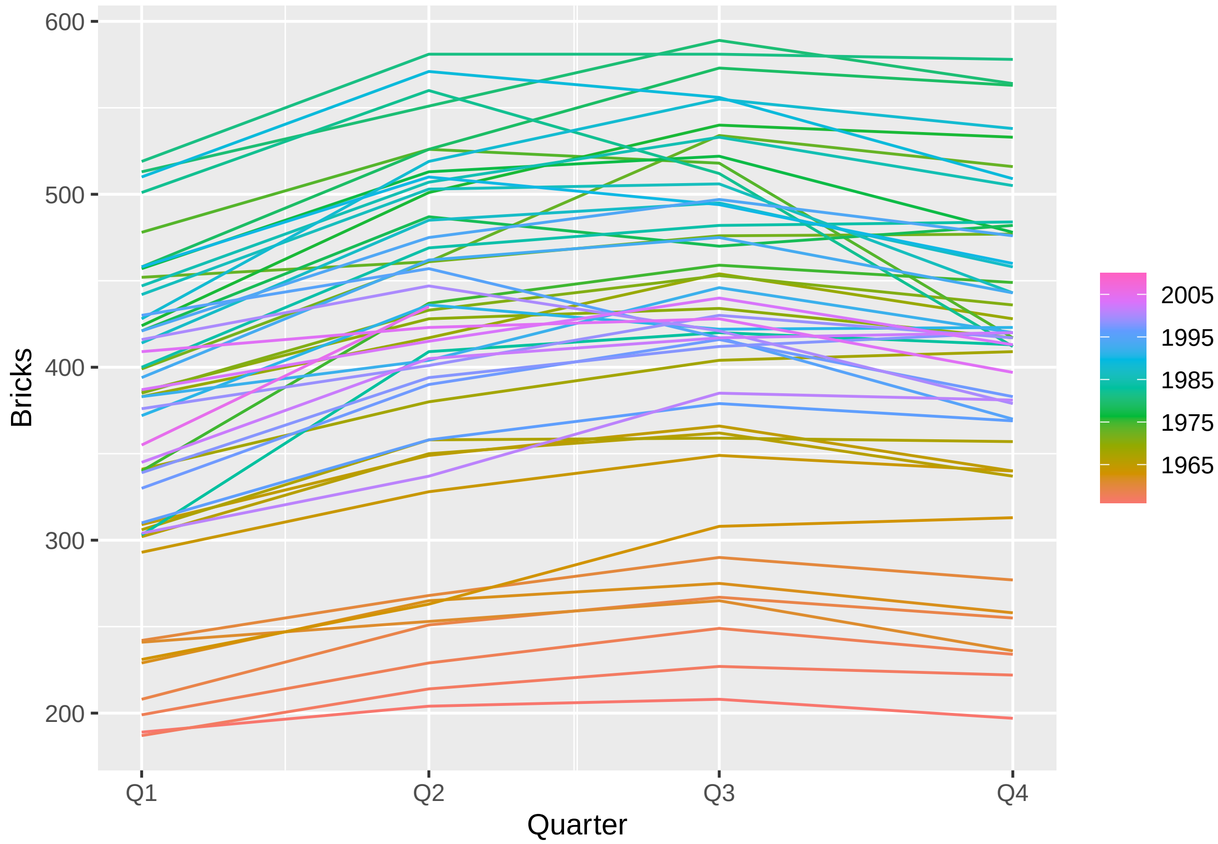
```
aus_production
```

```
## # A tsibble: 218 x 7 [1Q]
##    Quarter  Beer Tobacco Bricks Cement Electricity   Gas
##      <qtr> <dbl>   <dbl>  <dbl>  <dbl>       <dbl> <dbl>
##  1 1956 Q1   284    5225    189    465        3923     5
##  2 1956 Q2   213    5178    204    532        4436     6
##  3 1956 Q3   227    5297    208    561        4806     7
##  4 1956 Q4   308    5681    197    570        4418     6
##  5 1957 Q1   262    5577    187    529        4339     5
##  6 1957 Q2   228    5651    214    604        4811     7
##  7 1957 Q3   236    5317    227    603        5259     7
##  8 1957 Q4   320    6152    222    582        4735     6
##  9 1958 Q1   272    5758    199    554        4608     5
## 10 1958 Q2   233    5641    229    620        5196     7
## # i 208 more rows
```

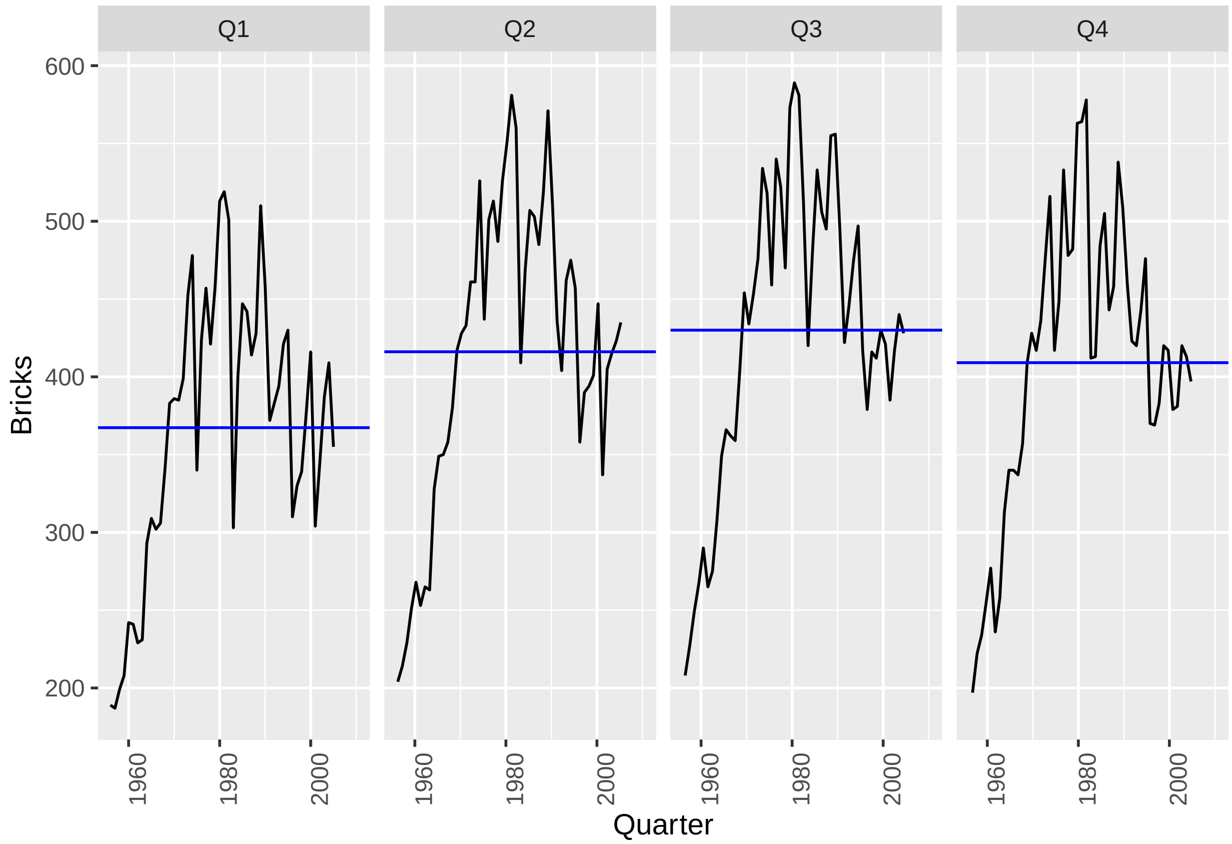
```
autoplot(aus_production, Bricks)
```



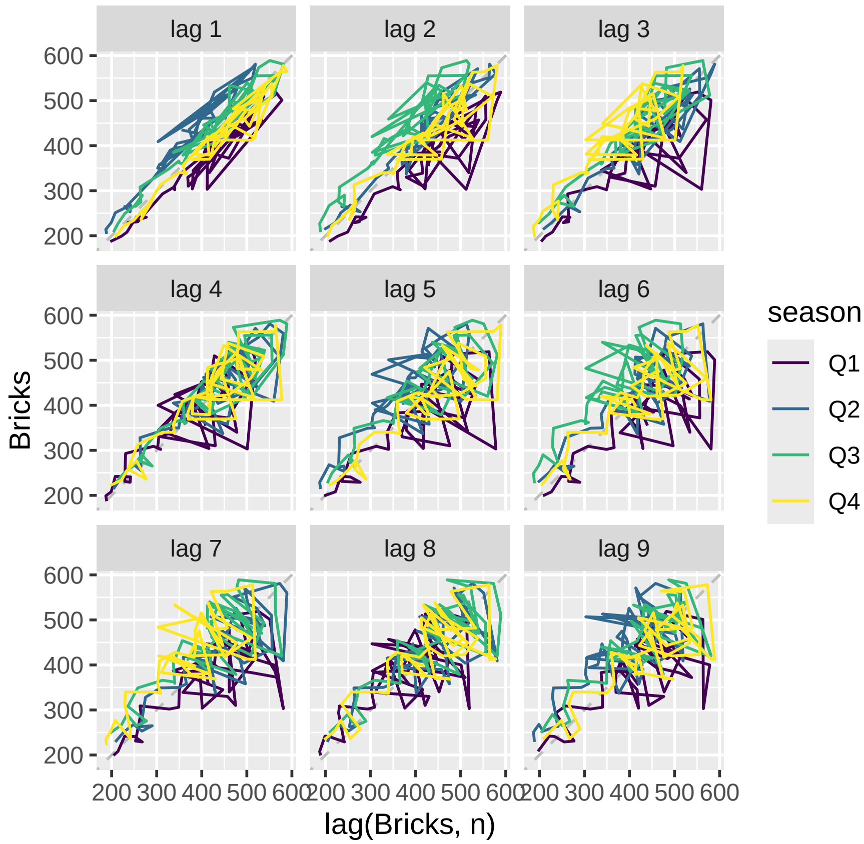

```
gg_season(aus_production, y = Bricks)
```



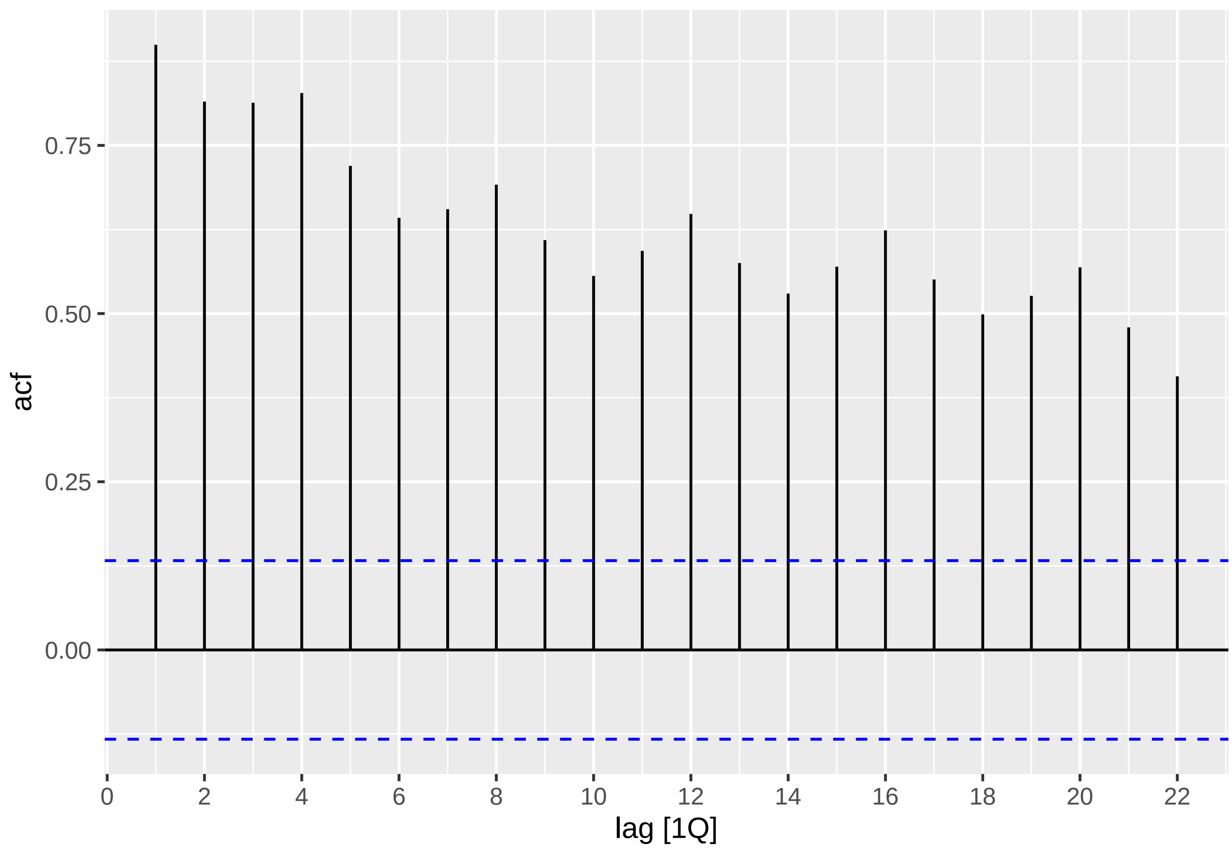

```
gg_subseries(aus_production, y = Bricks)
```




```
gg_lag(aus_production, y = Bricks)
```




```r
ACF(aus_production, y = Bricks) %>%
  autoplot()
```

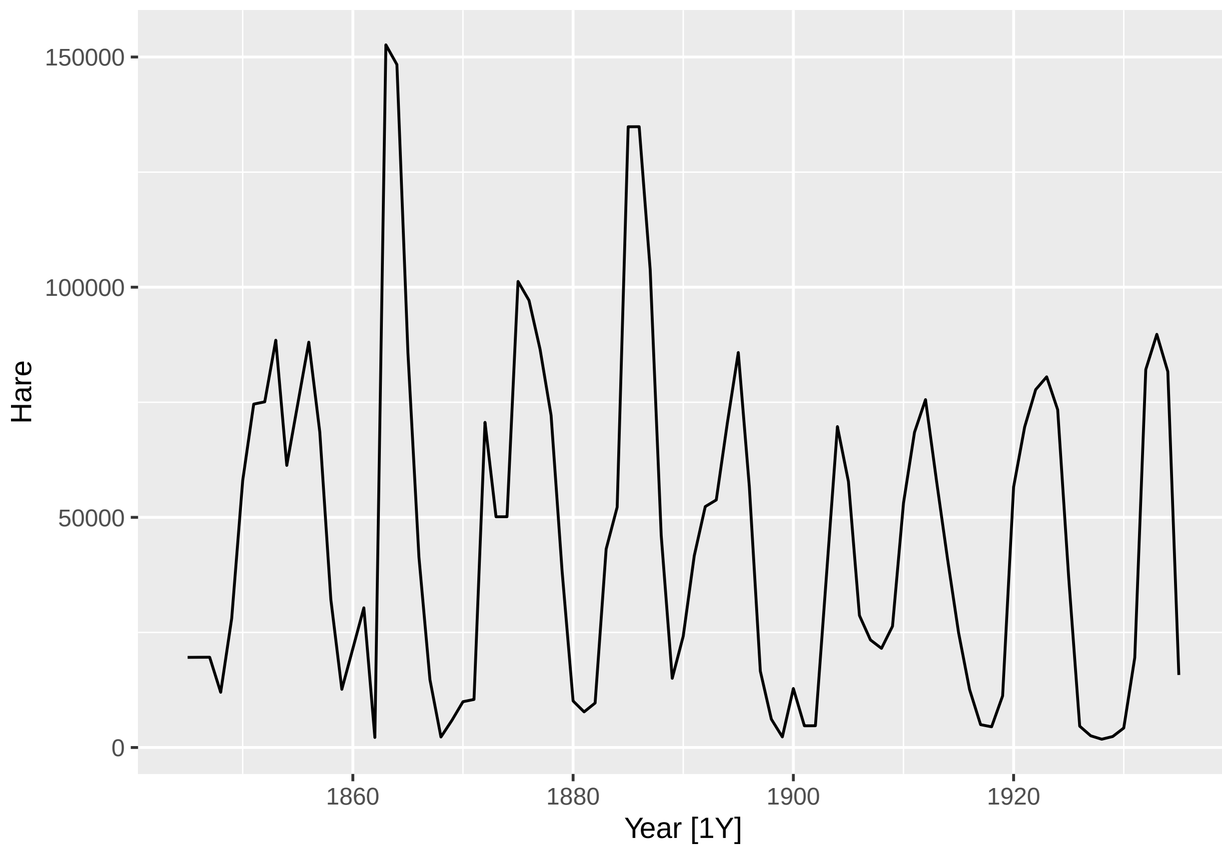


As can be seen above, the `Bricks` time series from `aus_production` gives clear signs of seasonality where the number of bricks produced goes up in quarters two and three to drop dramatically towards the beginning of the following year. The series was cyclical every few years and had some especially hard dips around the years 1975, 1983, 1991, and 1996. The over all trend began positive up until around 1983 where things began going south. This could probably be due to consumer demand for bricks decreasing throughout the last few decades.

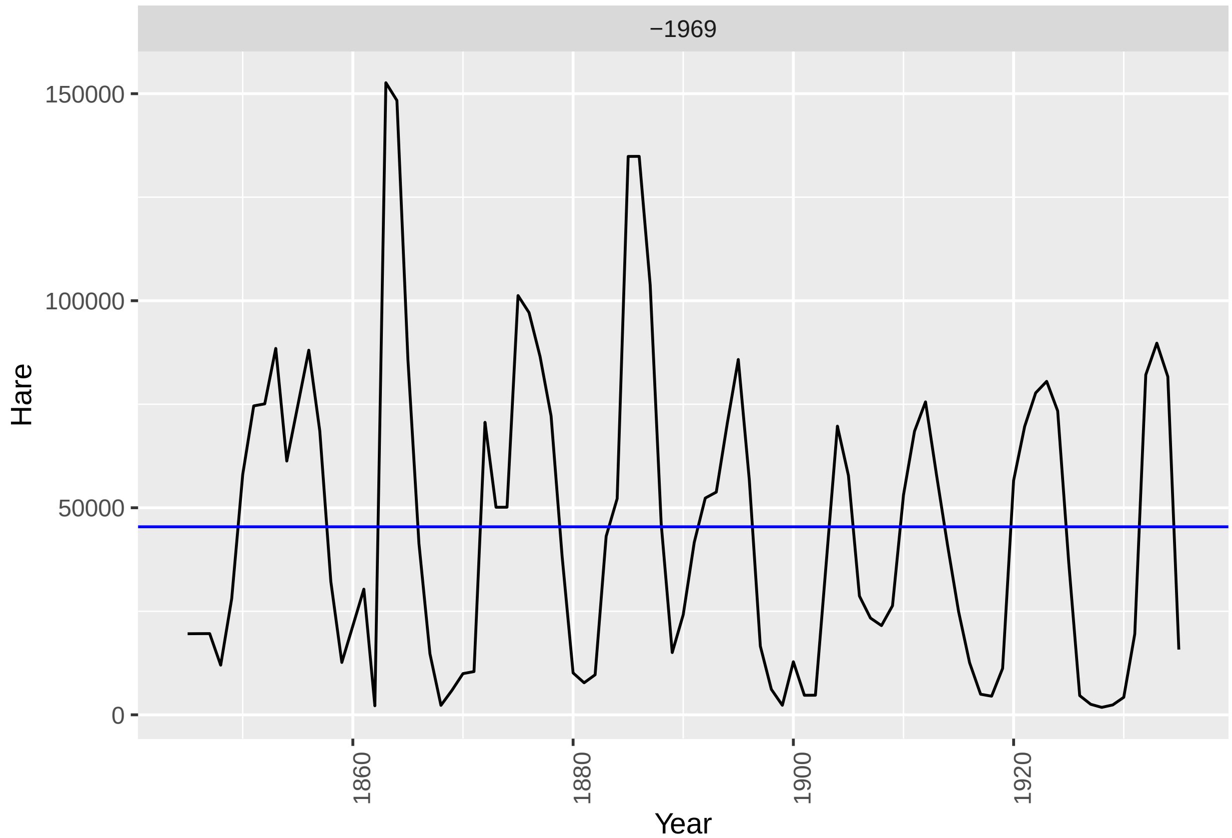
```
pelt
```

```
## # A tsibble: 91 x 3 [1Y]
##     Year  Hare  Lynx
##    <dbl> <dbl> <dbl>
##  1  1845 19580 30090
##  2  1846 19600 45150
##  3  1847 19610 49150
##  4  1848 11990 39520
##  5  1849 28040 21230
##  6  1850 58000  8420
##  7  1851 74600  5560
##  8  1852 75090  5080
##  9  1853 88480 10170
## 10  1854 61280 19600
## # i 81 more rows
```

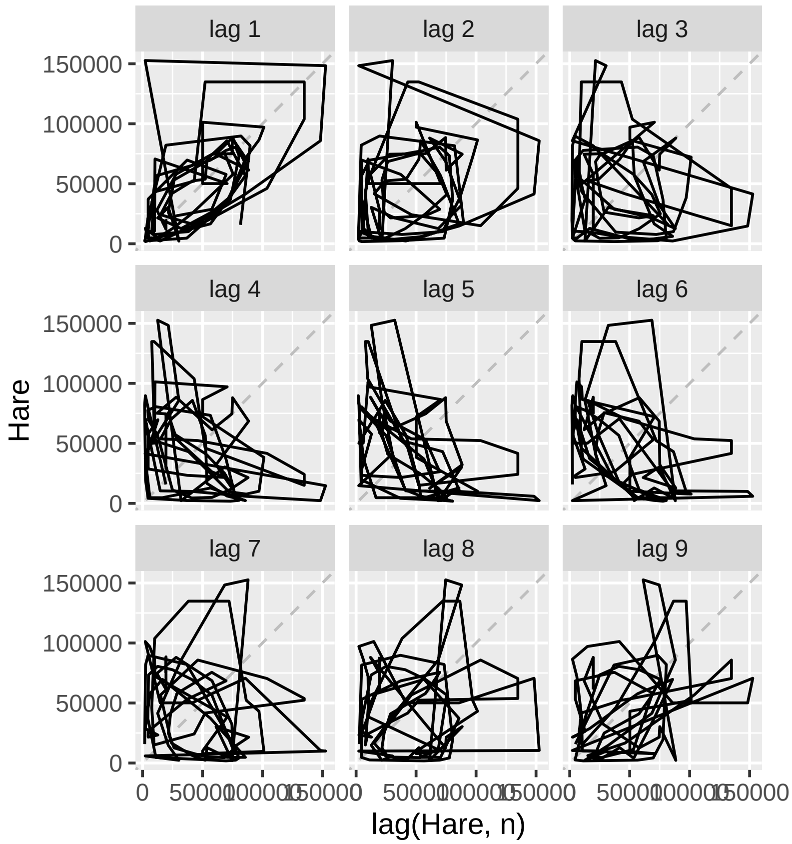
```
autoplot(pelt, Hare)
```



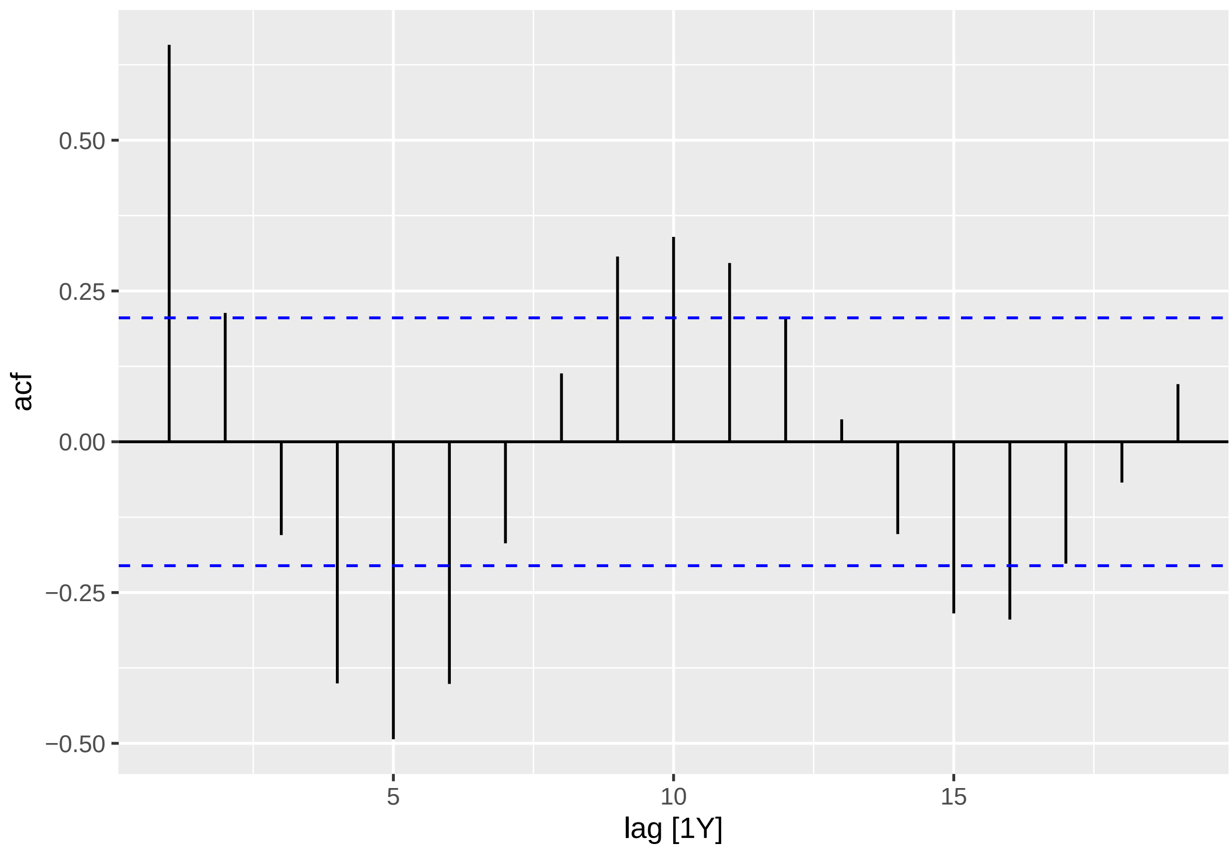

```
#gg_season(pelt, y = Hare, period = "year") Couldn't get it to work :(
gg_subseries(pelt, y = Hare)
```




```
gg_lag(pelt, y = Hare)
```




```r
ACF(pelt, y = Hare) %>%
  autoplot()
```

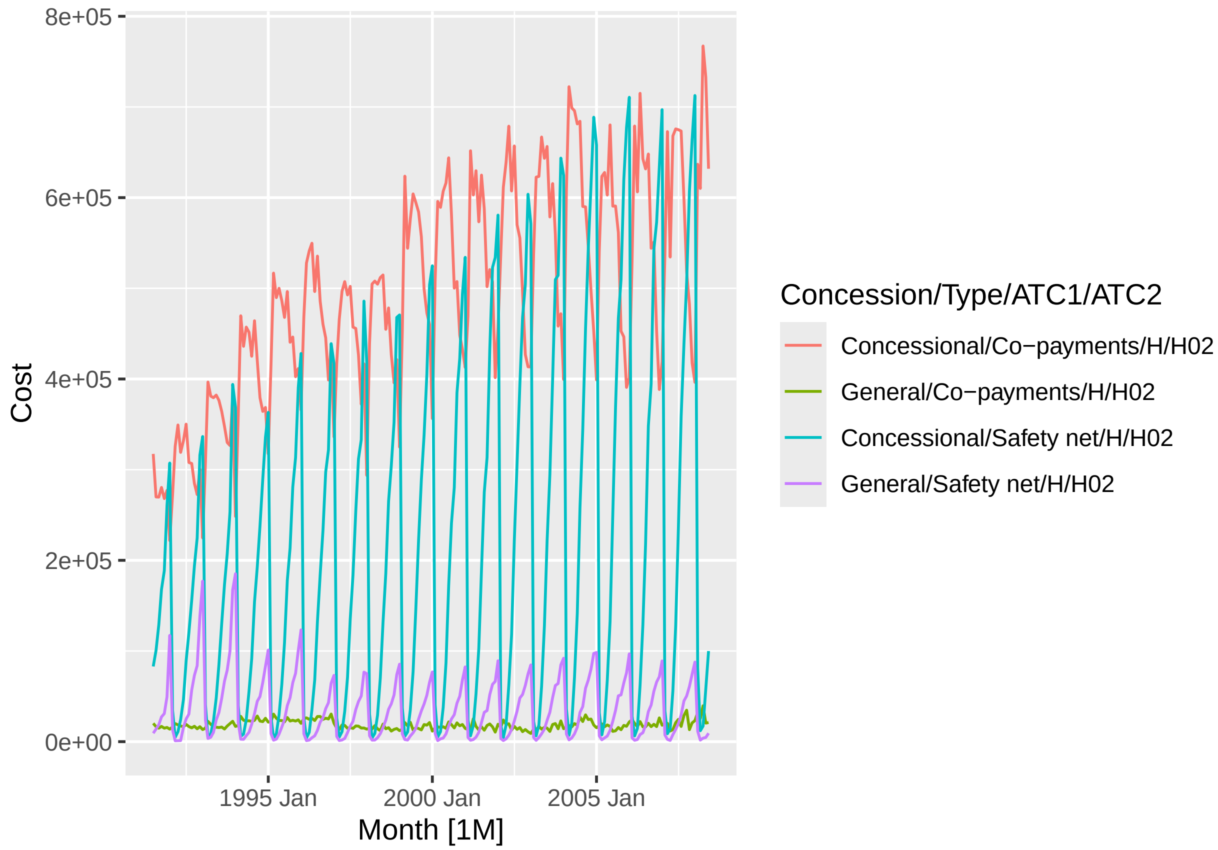


As can be seen above, the `Hare` time series from `pelt` shows very little, f any, signs of seasonality. Seasonality can only be defined within a year, whether it be quarterly, monthly, or weekly. This time series does not show to have yearly patterns but rather a pattern that seems to last around 10 years at a time. This pattern can be better described as cyclical. With regards to trend, there seems to be no indication of one, whether positive or negative. This series is best defined as a pattern of habitual decade long cycles repeating nonstop.

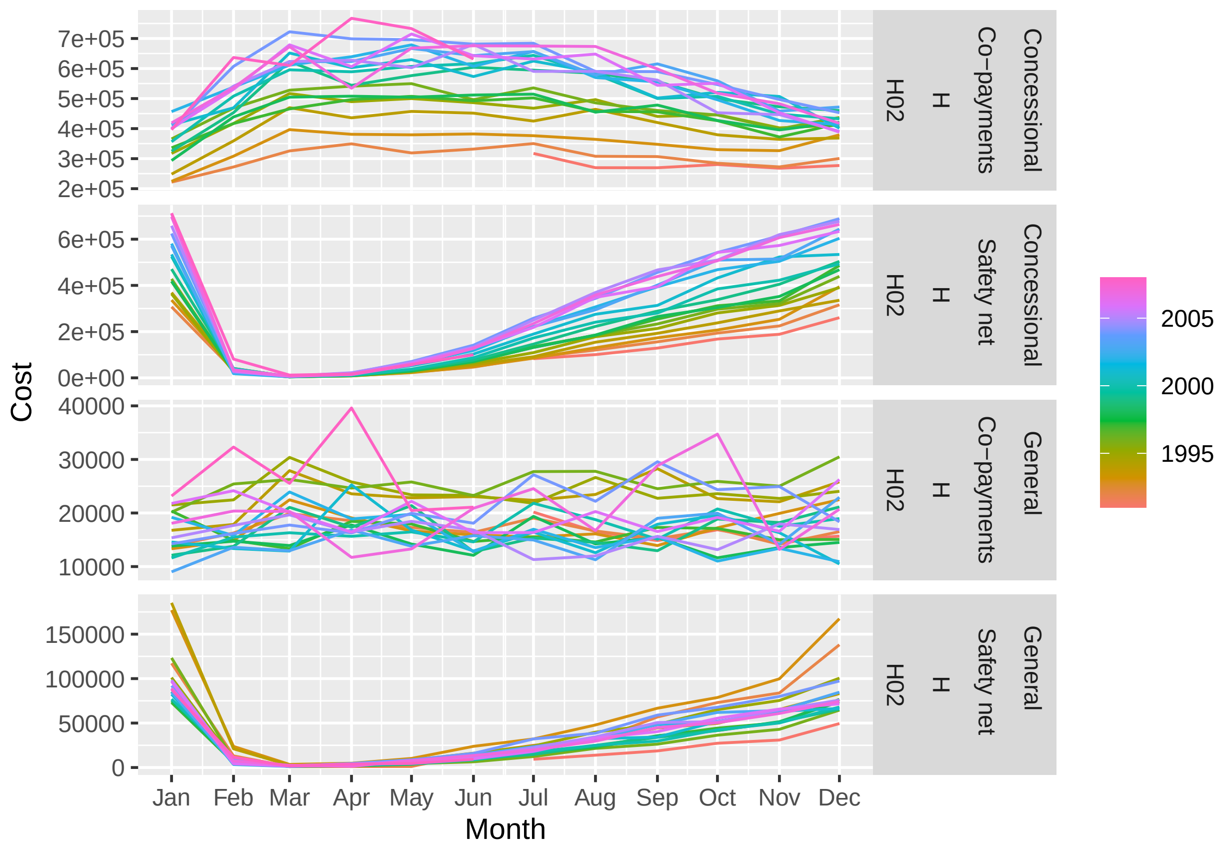
```
PBS
```

```
## # A tsibble: 67,596 x 9 [1M]
## # Key:       Concession, Type, ATC1, ATC2 [336]
##       Month Concession   Type      ATC1  ATC1_desc ATC2  ATC2_desc Scripts  Cost
##       <mth> <chr>        <chr>     <chr> <chr>     <chr> <chr>       <dbl> <dbl>
##  1 1991 Jul Concessional Co-payme~ A     Alimenta~ A01   STOMATOL~   18228 67877
##  2 1991 Aug Concessional Co-payme~ A     Alimenta~ A01   STOMATOL~   15327 57011
##  3 1991 Sep Concessional Co-payme~ A     Alimenta~ A01   STOMATOL~   14775 55020
##  4 1991 Oct Concessional Co-payme~ A     Alimenta~ A01   STOMATOL~   15380 57222
##  5 1991 Nov Concessional Co-payme~ A     Alimenta~ A01   STOMATOL~   14371 52120
##  6 1991 Dec Concessional Co-payme~ A     Alimenta~ A01   STOMATOL~   15028 54299
##  7 1992 Jan Concessional Co-payme~ A     Alimenta~ A01   STOMATOL~   11040 39753
##  8 1992 Feb Concessional Co-payme~ A     Alimenta~ A01   STOMATOL~   15165 54405
##  9 1992 Mar Concessional Co-payme~ A     Alimenta~ A01   STOMATOL~   16898 61108
## 10 1992 Apr Concessional Co-payme~ A     Alimenta~ A01   STOMATOL~   18141 65356
## # i 67,586 more rows
```

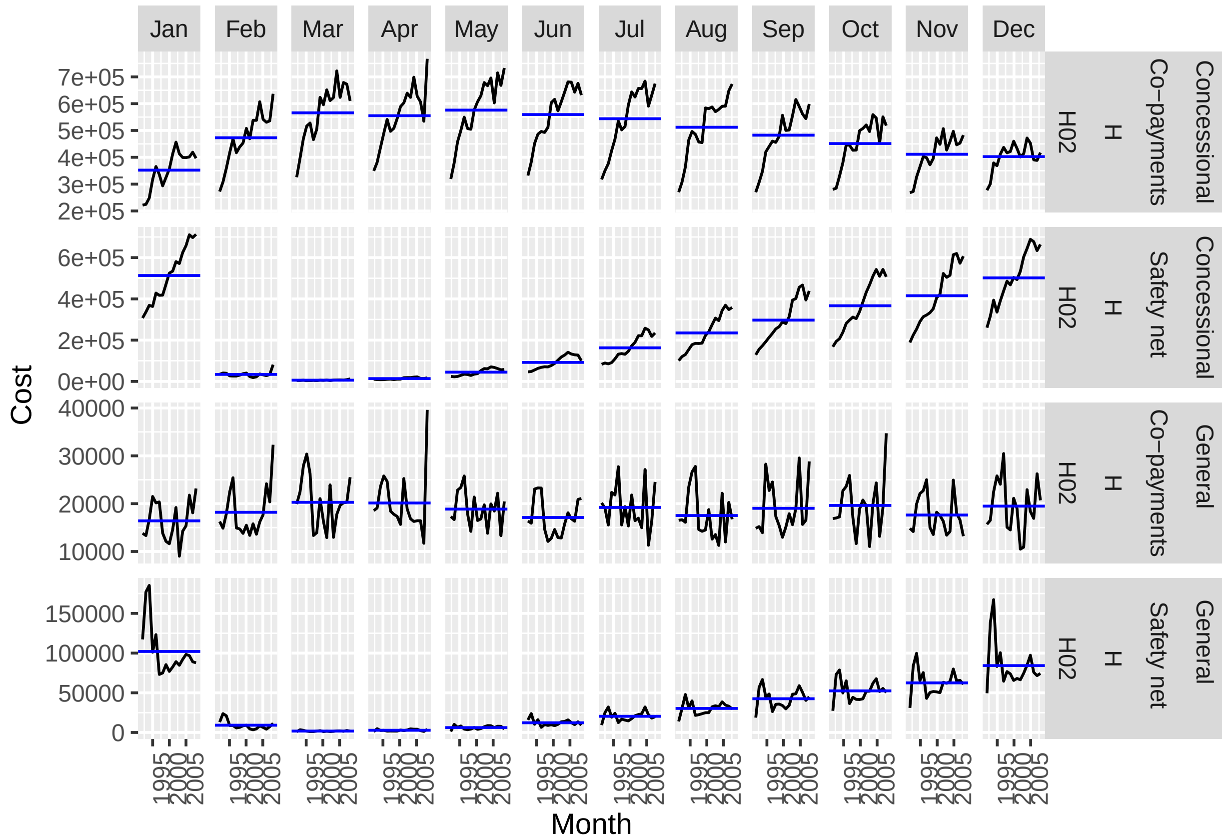
```r
H02 <- PBS %>%
  filter(ATC2 == "H02")
autoplot(H02, Cost)
```



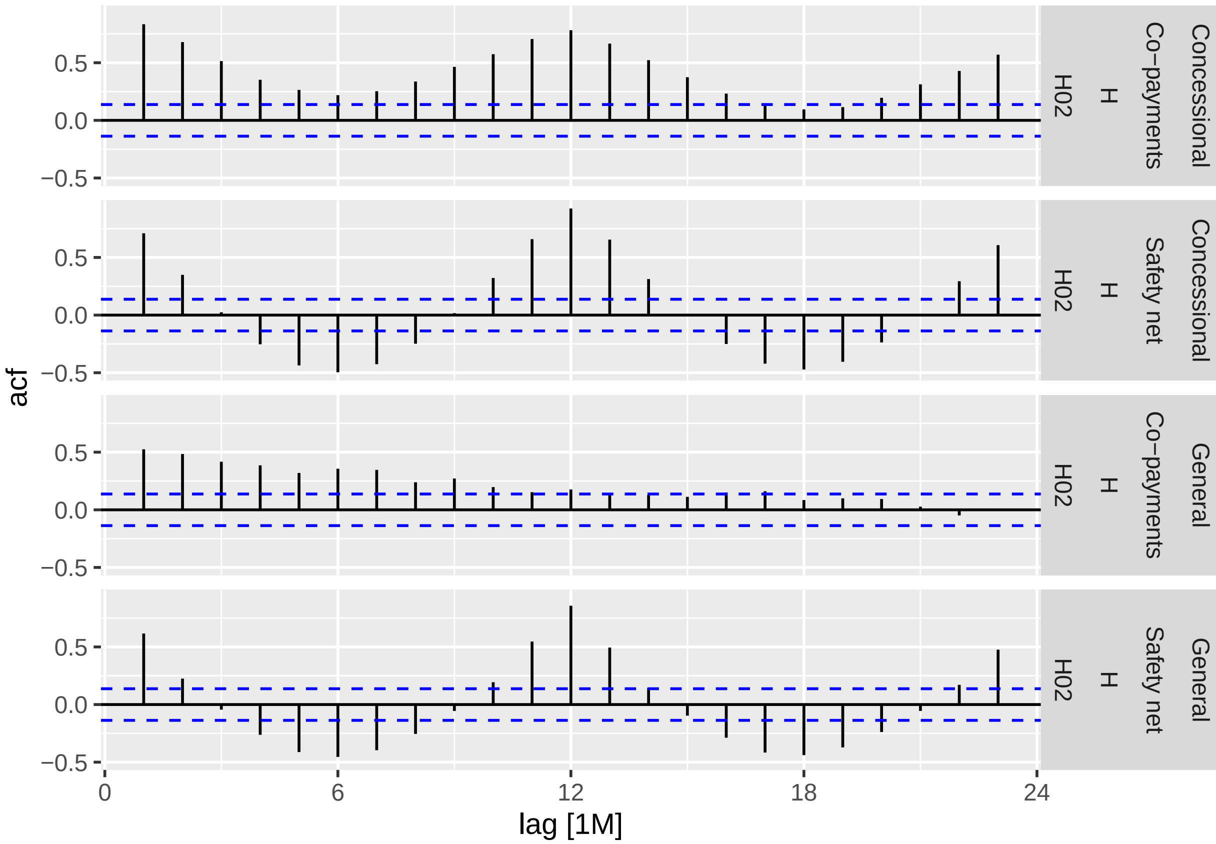

```r
gg_season(H02, y = Cost)
```




```r
gg_subseries(H02, y = Cost)
```




```r
#gg_lag(H02, y = Cost) Couldn't get it to work :(
ACF(H02, y = Cost) %>%
  autoplot()
```

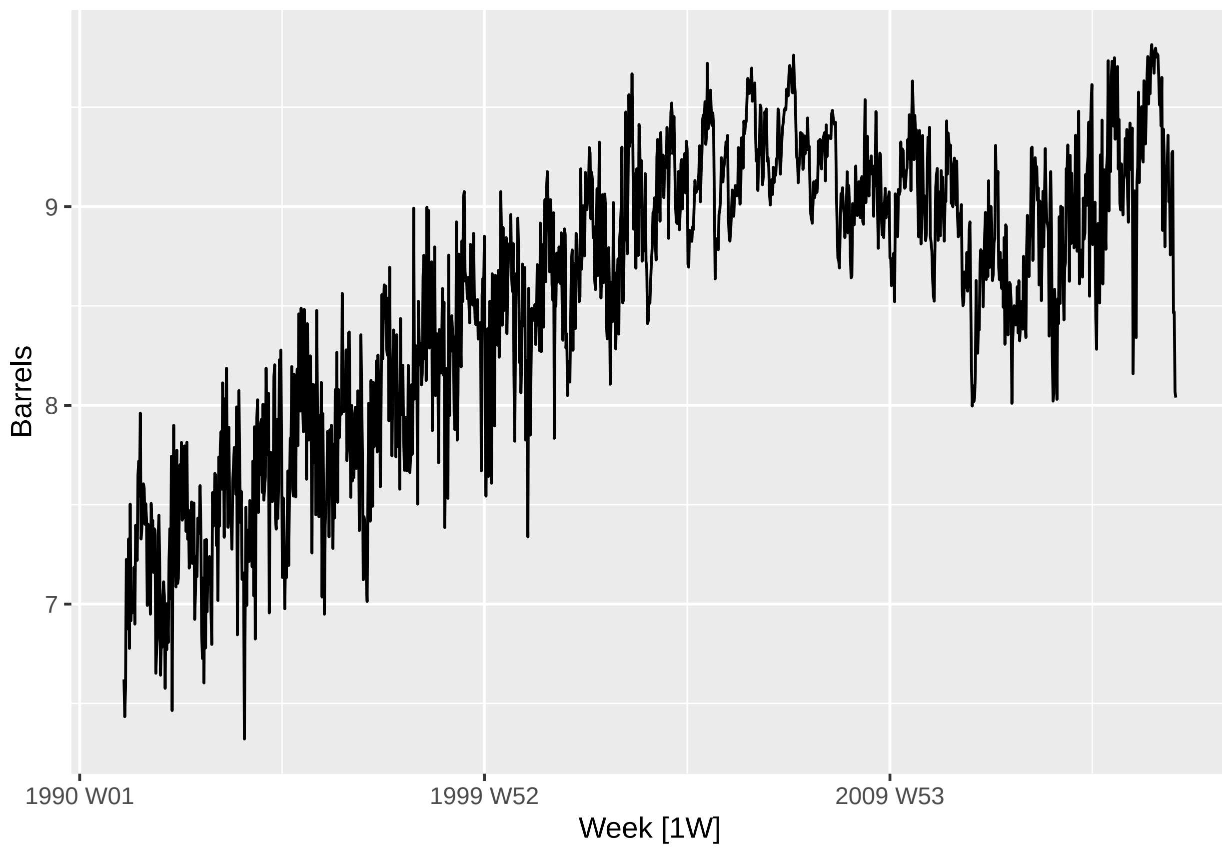


As can be seen above, the "H02" `Cost` time series from `PBS` is seasonal for some `Concession/Type` combinations but not for all. Right off the bat we can see in the `gg_season` and `gg_subseries` plots that general/co_payments combination is not seasonal, while the rest are. Concessional/co-payments seems to rise throughout the middle months, concessional/safety net seems to dip during the middle months, and general/safety net seems to rise slightly during the final months of the year. Given the above plots, we can't say for sure whether there is a cycle since the fluctuations seen can be explained by the seasonality mentioned earlier. There are noticeable trends with concessional/co_payments and concessional/safety net moving in the positive throughout the years while general_co-payments and general/safety net remain about the same.

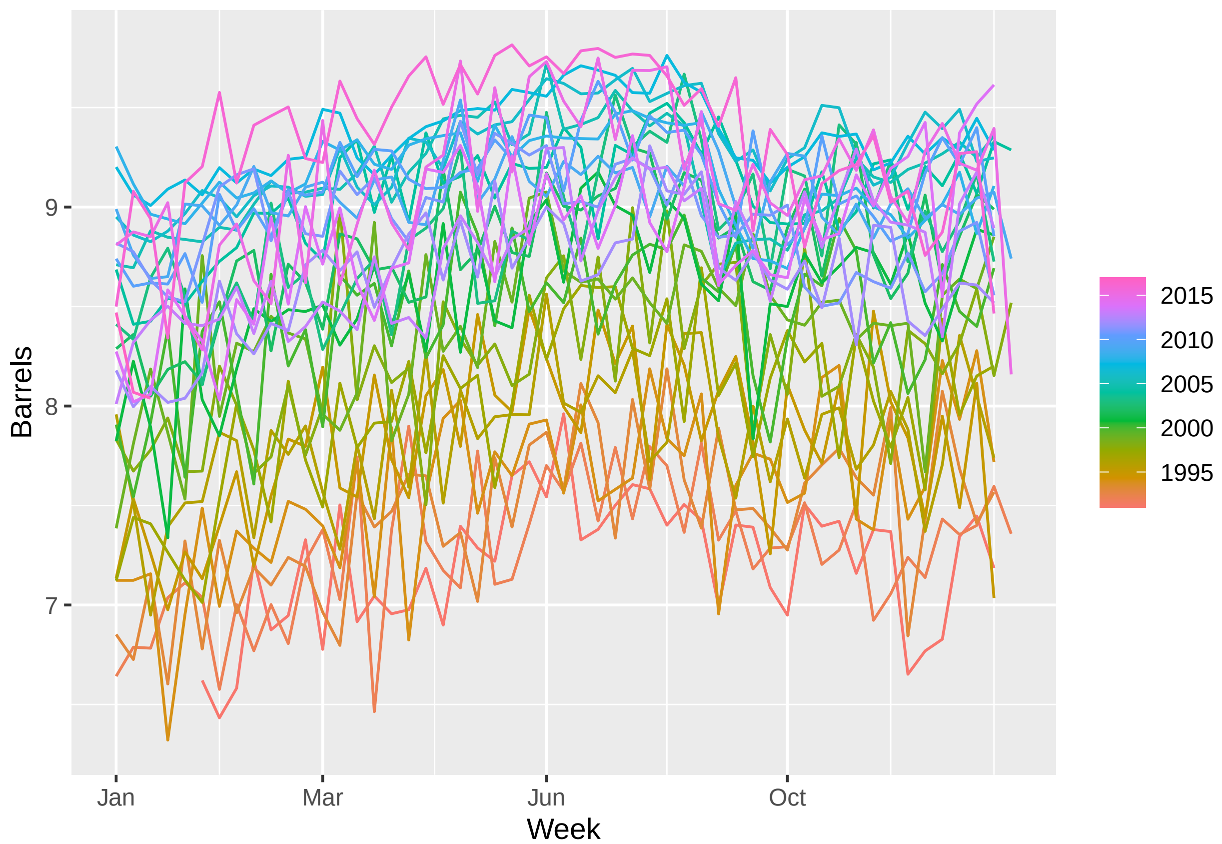
```
us_gasoline
```

```
## # A tsibble: 1,355 x 2 [1W]
##        Week Barrels
##      <week>   <dbl>
##  1 1991 W06    6.62
##  2 1991 W07    6.43
##  3 1991 W08    6.58
##  4 1991 W09    7.22
##  5 1991 W10    6.88
##  6 1991 W11    6.95
##  7 1991 W12    7.33
##  8 1991 W13    6.78
##  9 1991 W14    7.50
## 10 1991 W15    6.92
## # i 1,345 more rows
```

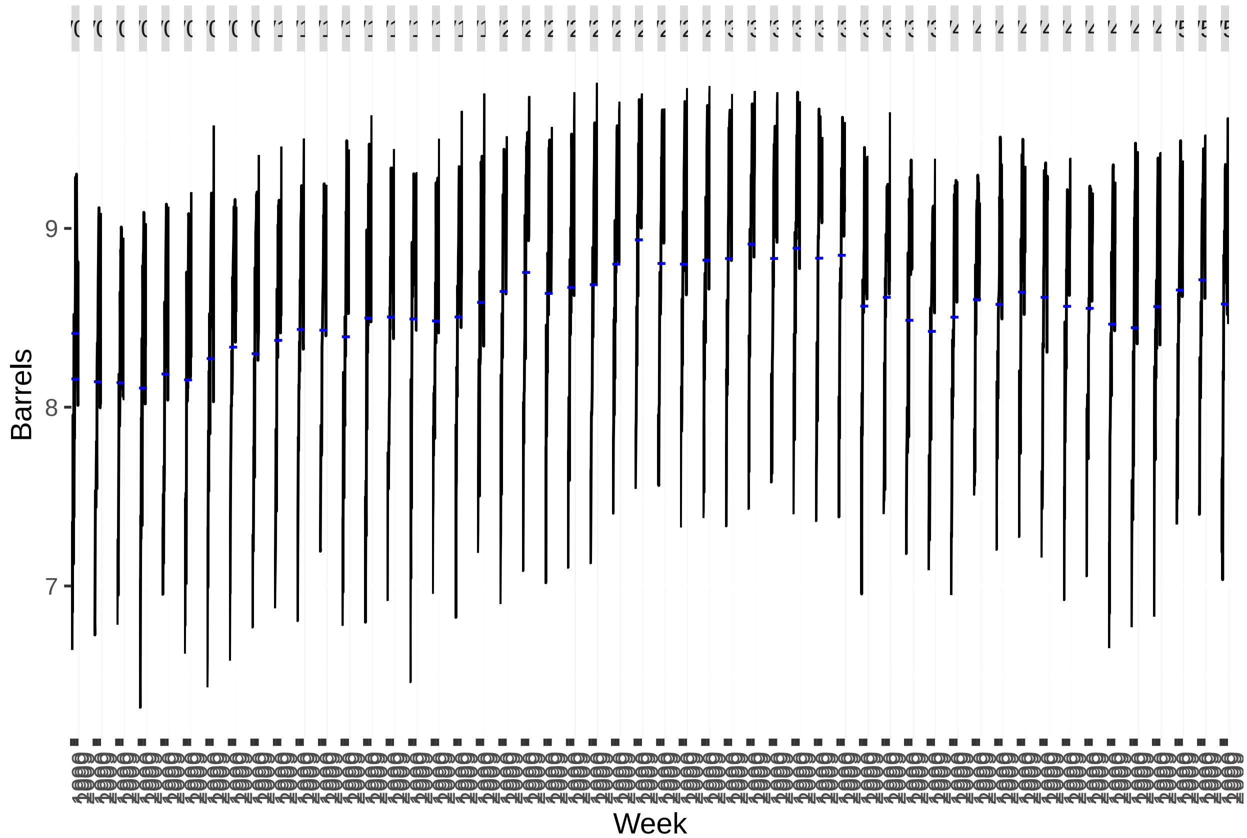
```r
autoplot(us_gasoline, Barrels)
```



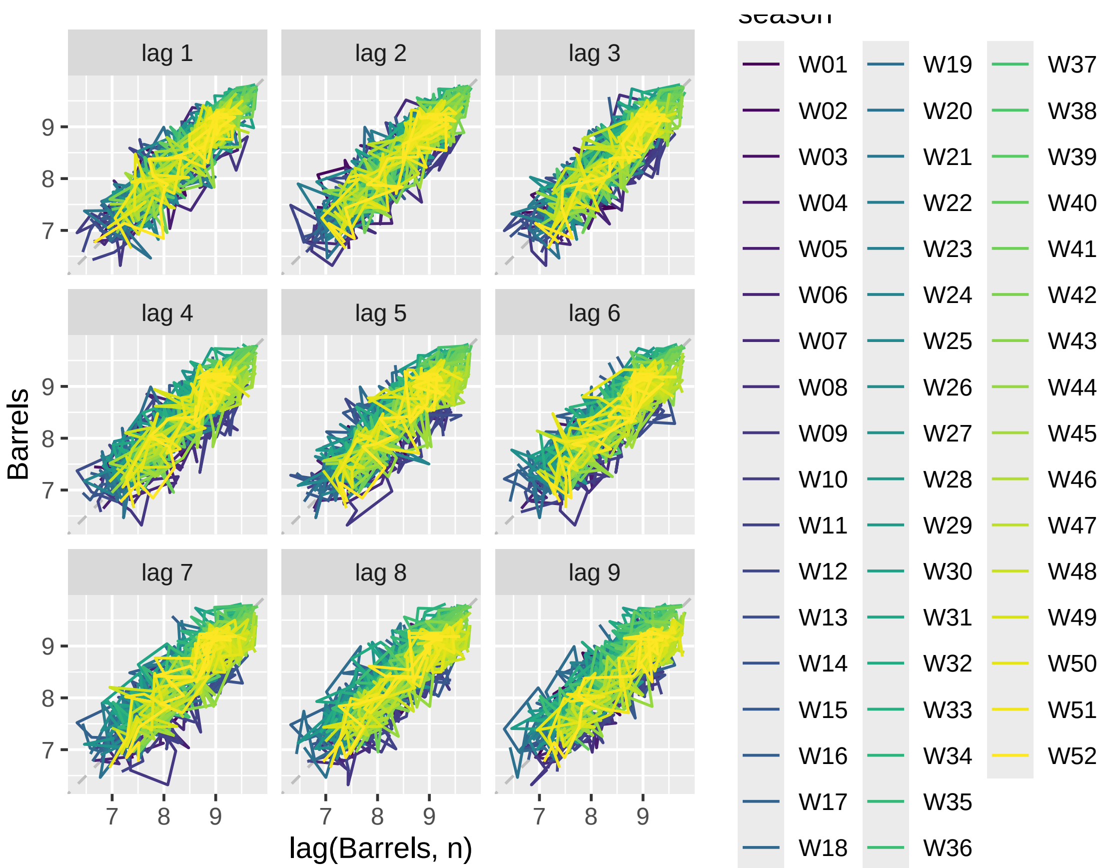

```r
gg_season(us_gasoline, y = Barrels)
```



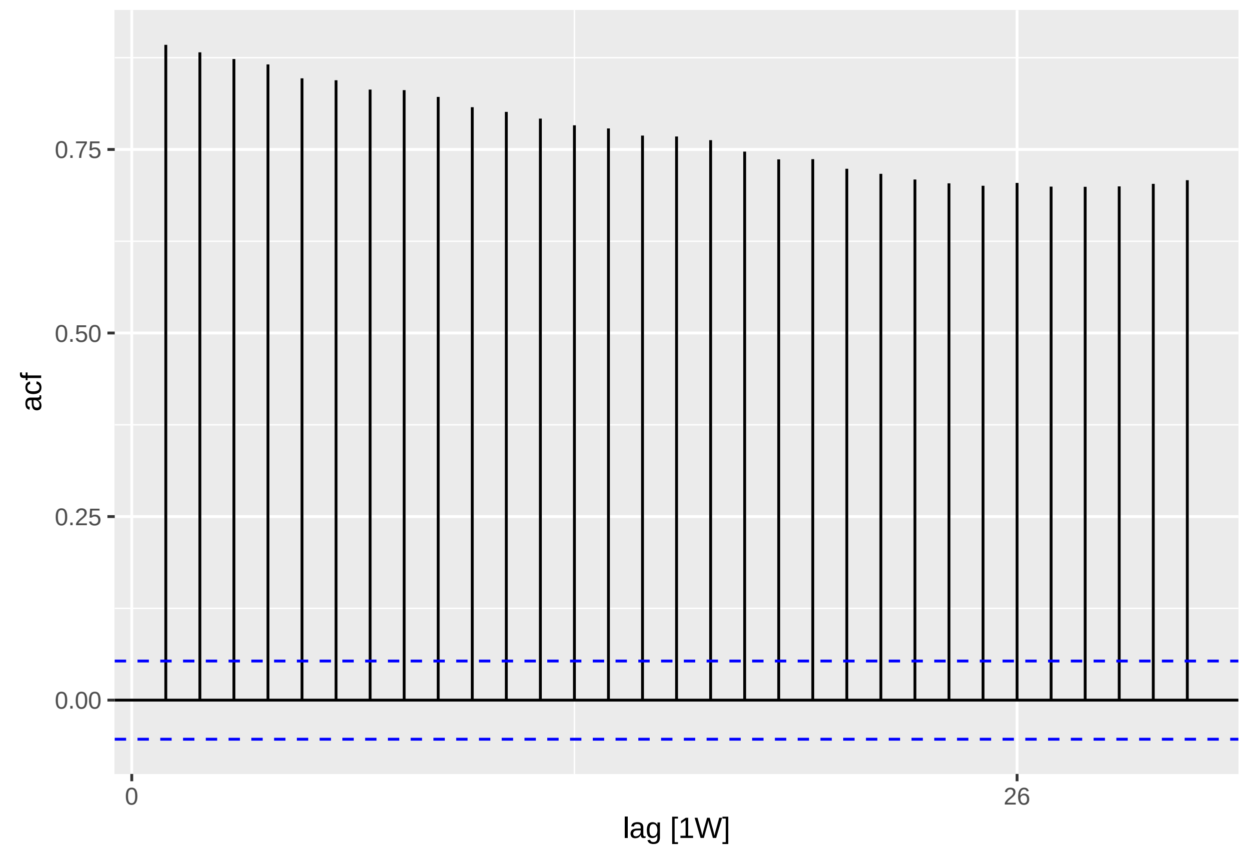

```
gg_subseries(us_gasoline, y = Barrels)
```




```r
gg_lag(us_gasoline, y = Barrels)
```




```
ACF(us_gasoline, y = Barrels) %>%
  autoplot()
```



As can be seen above, the `Barrels` time series from `us_gasoline` does seem to show slight seasonality with the barrels sold between the months of March and October bumping up and going back down shortly after. There don't seem to be any prominent cycles except for the dip observed around the years 2007 to 2013 which was most likely caused by the economic recession of 2008. The overall trend, however, is positive and it seems that US gasoline consumption managed to recover from the downturn.

Works Cited

History.com Editors. (2019, October 11). Great Recession. HISTORY; A&E Television Networks. https://www.history.com/topics/21st-century/recession