

# Time Series Analysis & Forecasting Using R

## 9. Dynamic regression



# Outline

1 Regression with ARIMA errors

2 Lab Session 18

3 Dynamic harmonic regression

4 Lab Session 19

5 Lagged predictors

# Outline

1 Regression with ARIMA errors

2 Lab Session 18

3 Dynamic harmonic regression

4 Lab Session 19

5 Lagged predictors

# Regression with ARIMA errors

## Regression models

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + \varepsilon_t,$$

- $y_t$  modeled as function of  $k$  explanatory variables
- In regression, we assume that  $\varepsilon_t$  is white noise.

# Regression with ARIMA errors

## Regression models

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + \varepsilon_t,$$

- $y_t$  modeled as function of  $k$  explanatory variables
- In regression, we assume that  $\varepsilon_t$  is white noise.

## RegARIMA model

$$y_t = \beta_0 + \beta_1 x_{1,t} + \cdots + \beta_k x_{k,t} + \eta_t,$$

$$\eta_t \sim \text{ARIMA}$$

- Residuals are from ARIMA model.
- Estimate model in one step using MLE
- Select model with lowest AICc value.

# US personal consumption and income

```
us_change
```

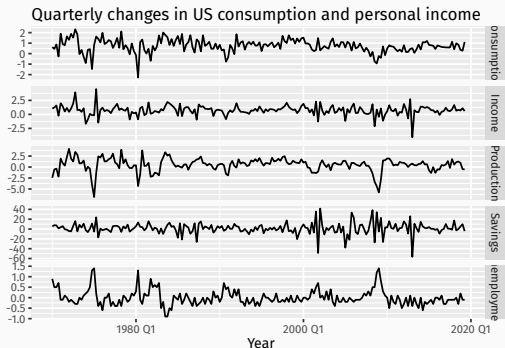
```
# A tsibble: 198 x 6 [1Q]
```

	Quarter	Consumption	Income	Production	Savings	Unemployment
	<qtr>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
1	1970 Q1	0.619	1.04	-2.45	5.30	0.9
2	1970 Q2	0.452	1.23	-0.551	7.79	0.5
3	1970 Q3	0.873	1.59	-0.359	7.40	0.5
4	1970 Q4	-0.272	-0.240	-2.19	1.17	0.700
5	1971 Q1	1.90	1.98	1.91	3.54	-0.100
6	1971 Q2	0.915	1.45	0.902	5.87	-0.100
7	1971 Q3	0.794	0.521	0.308	-0.406	0.100
8	1971 Q4	1.65	1.16	2.29	-1.49	0
9	1972 Q1	1.31	0.457	4.15	-4.29	-0.200
10	1972 Q2	1.89	1.03	1.89	-4.69	-0.100

```
# i 188 more rows
```

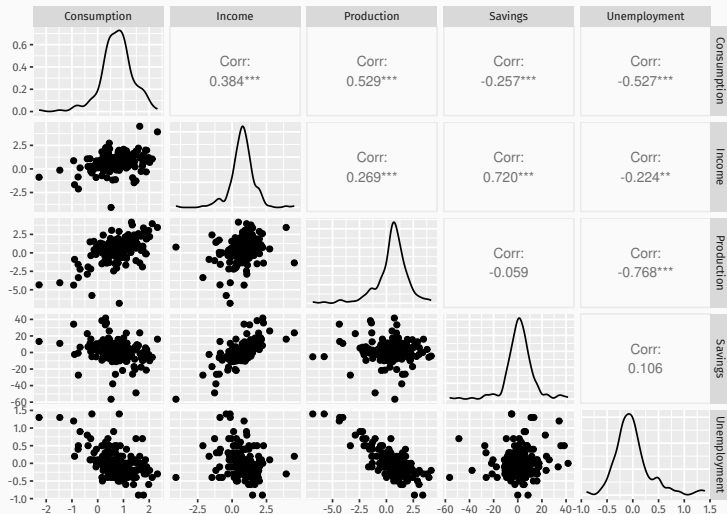
# US personal consumption and income

```
us_change |>  
  pivot_longer(-Quarter, names_to = "variable", values_to = "value") |>  
  ggplot(aes(y = value, x = Quarter, group = variable)) +  
  geom_line() + facet_grid(variable ~ ., scales = "free_y") +  
  labs(x = "Year", y = "",  
       title = "Quarterly changes in US consumption and personal income")
```



# US personal consumption and income

```
us_change |> as_tibble() |> select(-Quarter) |> GGally::ggpairs()
```





# US personal consumption and income

- No need for transformations or further differencing.
- Increase in income does not necessarily translate into instant increase in consumption (e.g., after the loss of a job, it may take a few months for expenses to be reduced to allow for the new circumstances). We will ignore this for now.

# US personal consumption and income

```
fit <- us_change |>
  model(regarima = ARIMA(Consumption ~ Income + Production + Savings +
                          Unemployment))
report(fit)
```

Series: Consumption

Model: LM w/ ARIMA(0,1,2) errors

Coefficients:

	ma1	ma2	Income	Production	Savings	Unemployment
	-1.0882	0.1118	0.7472	0.0370	-0.0531	-0.2096
s.e.	0.0692	0.0676	0.0403	0.0229	0.0029	0.0986

sigma^2 estimated as 0.09588: log likelihood=-47.1

AIC=108 AICc=109 BIC=131

# US personal consumption and income

```
fit <- us_change |>
  model(regarima = ARIMA(Consumption ~ Income + Production + Savings +
                          Unemployment))
report(fit)
```

Series: Consumption

Model: LM w/ ARIMA(0,1,2) errors

Coefficients:

	ma1	ma2	Income	Production	Savings	Unemployment
	-1.0882	0.1118	0.7472	0.0370	-0.0531	-0.2096
s.e.	0.0692	0.0676	0.0403	0.0229	0.0029	0.0986

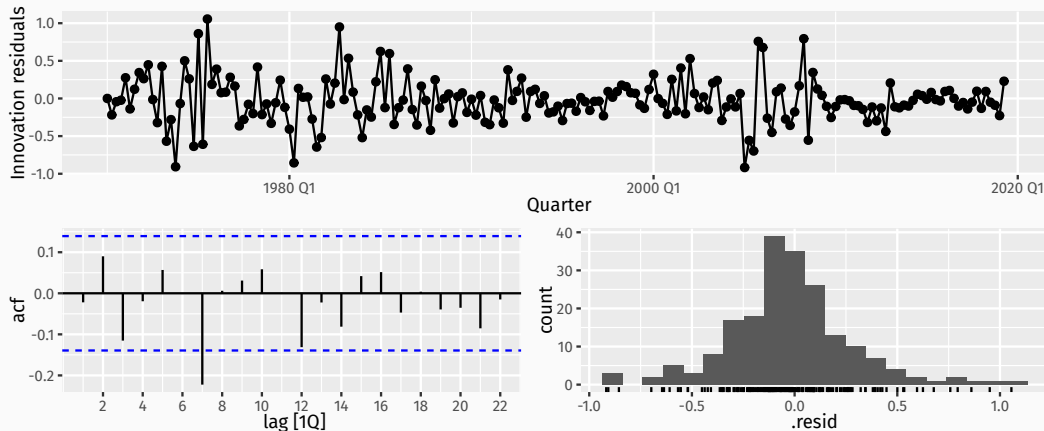
sigma^2 estimated as 0.09588: log likelihood=-47.1

AIC=108 AICc=109 BIC=131

Write down the equations for the fitted model.

# US personal consumption and income

```
gg_tsresiduals(fit)
```



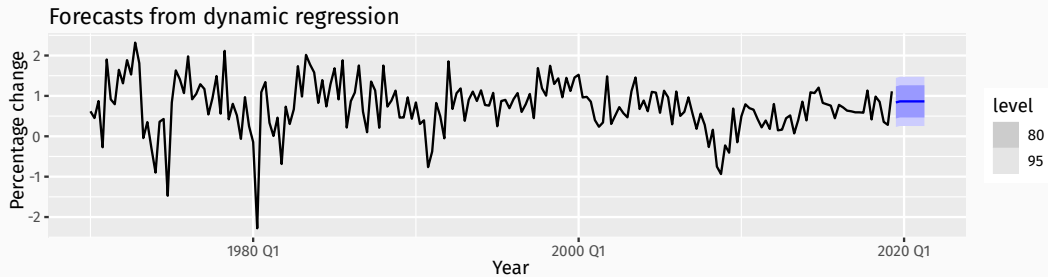
# US personal consumption and income

```
augment(fit) |>  
  features(.resid, ljung_box, dof = 2, lag = 12)
```

```
# A tibble: 1 x 3  
  .model    lb_stat lb_pvalue  
  <chr>      <dbl>    <dbl>  
1 regarima    20.0     0.0290
```

# US personal consumption and income

```
us_change_future <- new_data(us_change, 8) |>
  mutate(Income = tail(us_change$Income, 1),
         Production = tail(us_change$Production, 1),
         Savings = tail(us_change$Savings, 1),
         Unemployment = tail(us_change$Unemployment, 1))
forecast(fit, new_data = us_change_future) |>
  autoplot(us_change) +
  labs(x = "Year", y = "Percentage change",
       title = "Forecasts from dynamic regression")
```



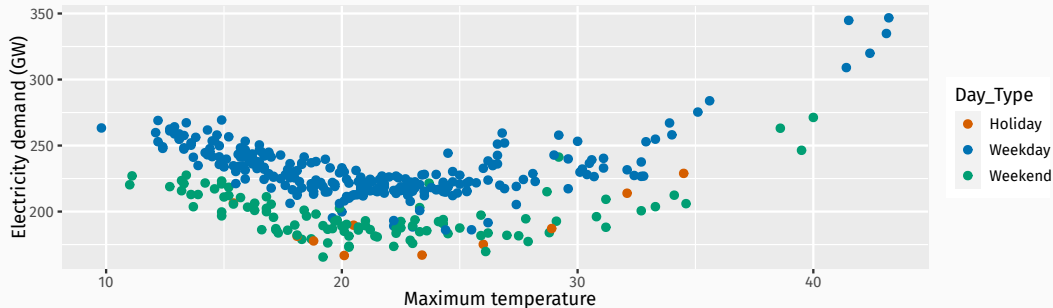
# Forecasting

- To forecast a regression model with ARIMA errors, we need to forecast the regression part of the model and the ARIMA part of the model and combine the results.
- Some predictors are known into the future (e.g., time, dummies).
- Separate forecasting models may be needed for other predictors.
- Forecast intervals ignore the uncertainty in forecasting the predictors.

# Daily electricity demand

Model daily electricity demand as a function of temperature using quadratic regression with ARMA errors.

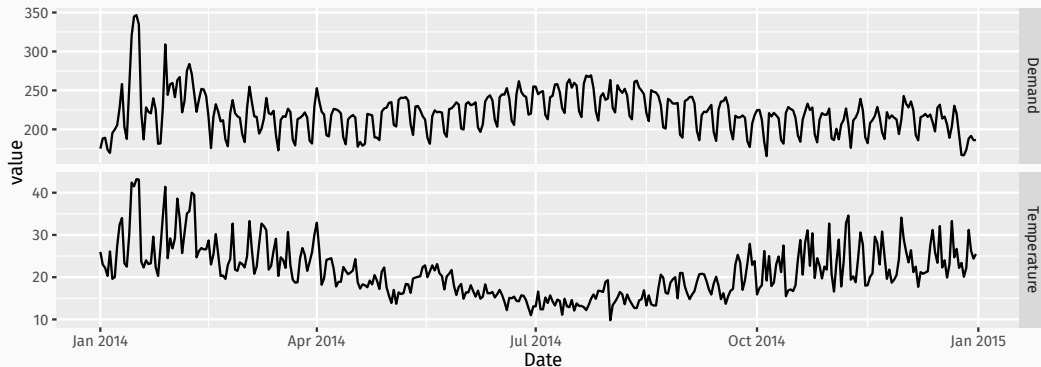
```
vic_elec_daily |>  
  ggplot(aes(x = Temperature, y = Demand, colour = Day_Type)) +  
  geom_point() +  
  labs(x = "Maximum temperature", y = "Electricity demand (GW)")
```





# Daily electricity demand

```
vic_elec_daily |>  
  pivot_longer(c(Demand, Temperature)) |>  
  ggplot(aes(x = Date, y = value)) +  
  geom_line() +  
  facet_grid(vars(name), scales = "free_y")
```



# Daily electricity demand

```
fit <- vic_elec_daily |>
  model(fit = ARIMA(Demand ~ Temperature + I(Temperature^2) +
    (Day_Type == "Weekday")))
report(fit)
```

Series: Demand

Model: LM w/ ARIMA(2,1,2)(2,0,0)[7] errors

Coefficients:

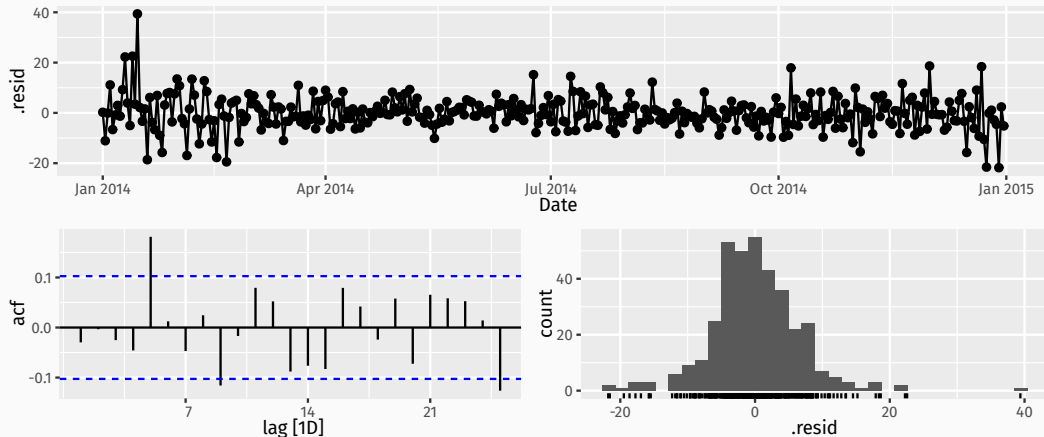
	ar1	ar2	ma1	ma2	sar1	sar2	Temperature	I(Temperature^2)
	-0.1093	0.7226	-0.0182	-0.9381	0.1958	0.417	-7.614	0.1810
s.e.	0.0779	0.0739	0.0494	0.0493	0.0525	0.057	0.448	0.0085
	Day_Type == "Weekday"TRUE							
	30.40							
s.e.	1.33							

sigma^2 estimated as 44.91: log likelihood=-1206

AIC=2432 AICc=2433 BIC=2471

# Daily electricity demand

```
augment(fit) |>  
  gg_tsdisplay(.resid, plot_type = "histogram")
```



# Daily electricity demand

```
augment(fit) |>  
  features(.resid, ljung_box, dof = 9, lag = 14)
```

```
# A tibble: 1 x 3  
  .model lb_stat lb_pvalue  
  <chr>    <dbl>    <dbl>  
1 fit          28.4 0.0000304
```

# Daily electricity demand

```
# Forecast one day ahead
```

```
vic_next_day <- new_data(vic_elec_daily, 1) |>
```

```
  mutate(Temperature = 26, Day_Type = "Holiday")
```

```
forecast(fit, vic_next_day)
```

```
# A fable: 1 x 6 [1D]
```

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

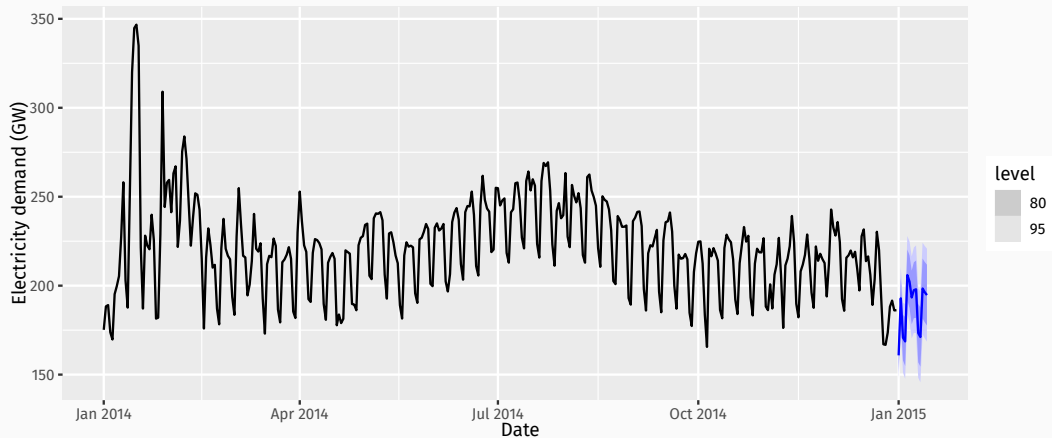
	.model	Date	Demand	.mean	Temperature	Day_Type
	<chr>	<date>	<dist>	<dbl>	<dbl>	<chr>
1	fit	2015-01-01	N(161, 45)	161.	26	Holiday

# Daily electricity demand

```
vic_elec_future <- new_data(vic_elec_daily, 14) |>
  mutate(
    Temperature = 26,
    Holiday = c(TRUE, rep(FALSE, 13)),
    Day_Type = case_when(
      Holiday ~ "Holiday",
      wday(Date) %in% 2:6 ~ "Weekday",
      TRUE ~ "Weekend"
    )
  )
```

# Daily electricity demand

```
forecast(fit, vic_elec_future) |>  
  autoplot(vic_elec_daily) + labs(y = "Electricity demand (GW)")
```



# Outline

1 Regression with ARIMA errors

2 Lab Session 18

3 Dynamic harmonic regression

4 Lab Session 19

5 Lagged predictors



# Lab Session 18

Repeat the daily electricity example, but instead of using a quadratic function of temperature, use a piecewise linear function with the “knot” around 20 degrees Celsius (use predictors Temperature & Temp2). How can you optimize the choice of knot?

```
vic_elec_daily <- vic_elec |>
  filter(year(Time) == 2014) |>
  index_by(Date = date(Time)) |>
  summarise(Demand = sum(Demand) / 1e3,
            Temperature = max(Temperature),
            Holiday = any(Holiday)
  ) |>
  mutate(Temp2 = I(pmax(Temperature - 20, 0)),
         Day_Type = case_when(
           Holiday ~ "Holiday",
           wday(Date) %in% 2:6 ~ "Weekday",
           TRUE ~ "Weekend")
  )
```

# Outline

1 Regression with ARIMA errors

2 Lab Session 18

3 Dynamic harmonic regression

4 Lab Session 19

5 Lagged predictors

# Dynamic harmonic regression

## Combine Fourier terms with ARIMA errors

### Advantages

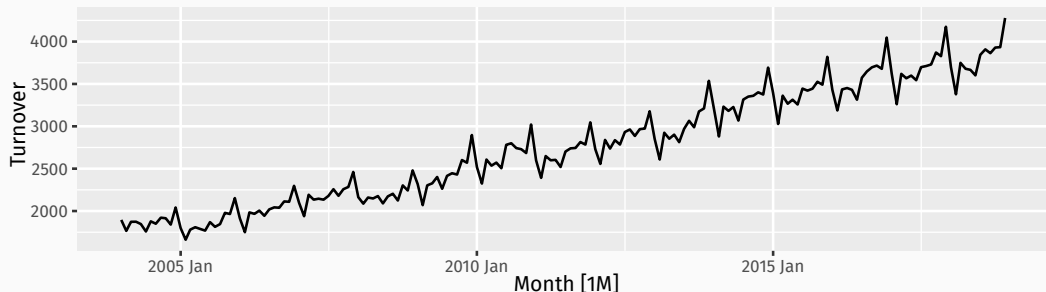
- it allows any length seasonality;
- for data with more than one seasonal period, you can include Fourier terms of different frequencies;
- the seasonal pattern is smooth for small values of  $K$  (but more wiggly seasonality can be handled by increasing  $K$ );
- the short-term dynamics are easily handled with a simple ARMA error.

### Disadvantages

- seasonality is assumed to be fixed

# Eating-out expenditure

```
aus_cafe <- aus_retail |>  
  filter(  
    Industry == "Cafes, restaurants and takeaway food services",  
    year(Month) %in% 2004:2018  
  ) |>  
  summarise(Turnover = sum(Turnover))  
aus_cafe |> autoplot(Turnover)
```

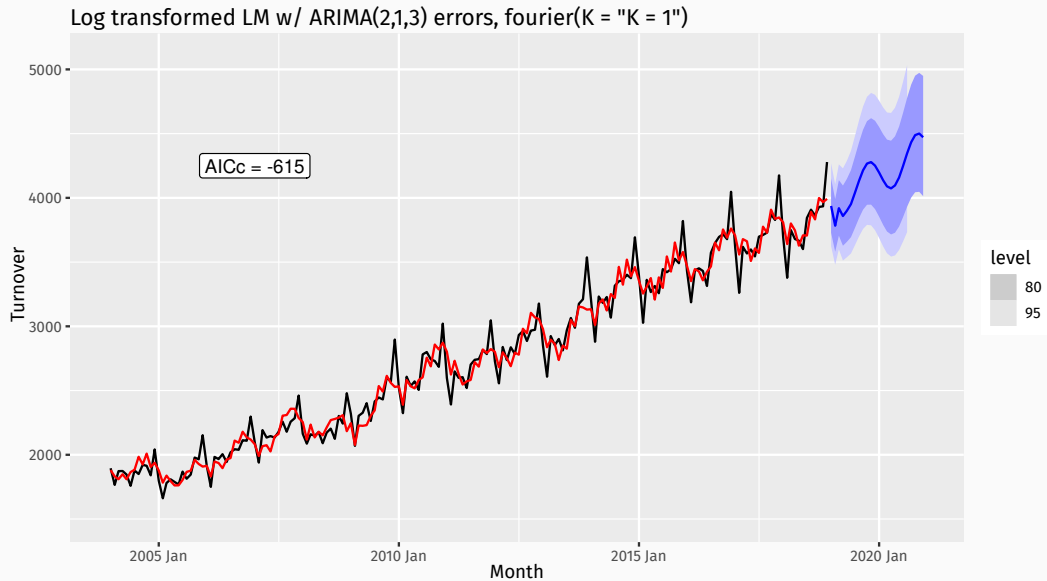


# Eating-out expenditure

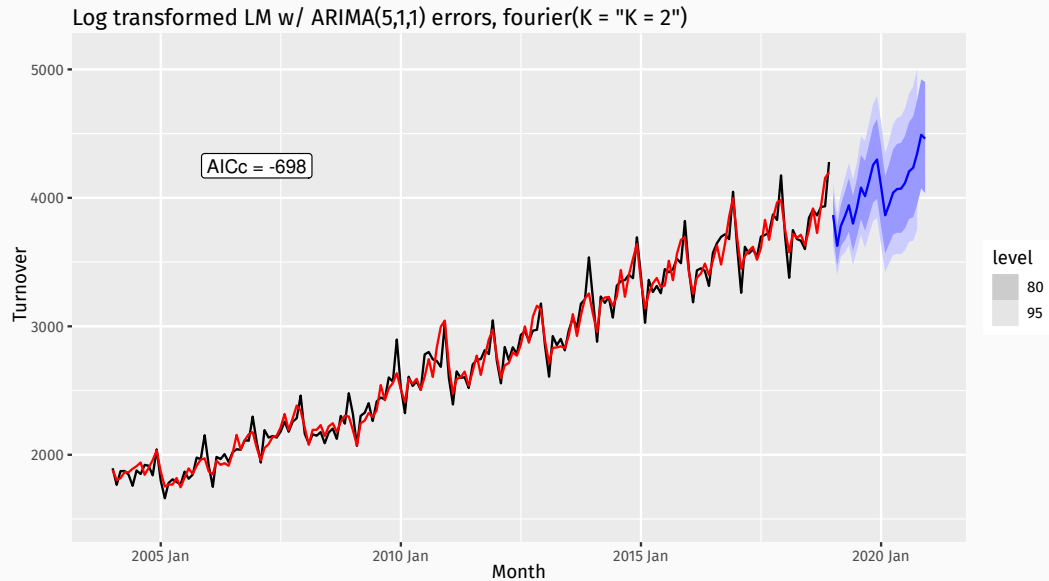
```
fit <- aus_cafe |> model(
  `K = 1` = ARIMA(log(Turnover) ~ fourier(K = 1) + PDQ(0, 0, 0)),
  `K = 2` = ARIMA(log(Turnover) ~ fourier(K = 2) + PDQ(0, 0, 0)),
  `K = 3` = ARIMA(log(Turnover) ~ fourier(K = 3) + PDQ(0, 0, 0)),
  `K = 4` = ARIMA(log(Turnover) ~ fourier(K = 4) + PDQ(0, 0, 0)),
  `K = 5` = ARIMA(log(Turnover) ~ fourier(K = 5) + PDQ(0, 0, 0)),
  `K = 6` = ARIMA(log(Turnover) ~ fourier(K = 6) + PDQ(0, 0, 0))
)
glance(fit)
```

.model	sigma2	log_lik	AIC	AICc	BIC
K = 1	0.002	317	-616	-615	-588
K = 2	0.001	362	-700	-698	-661
K = 3	0.001	394	-763	-761	-725
K = 4	0.001	427	-822	-818	-771
K = 5	0.000	474	-919	-917	-875
K = 6	0.000	474	-920	-918	-875

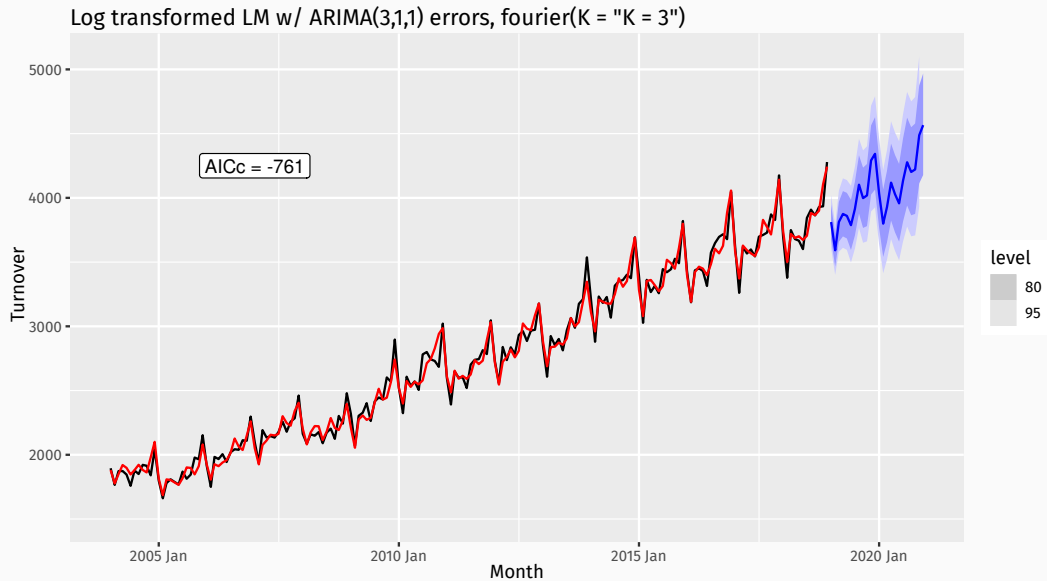
# Eating-out expenditure



# Eating-out expenditure

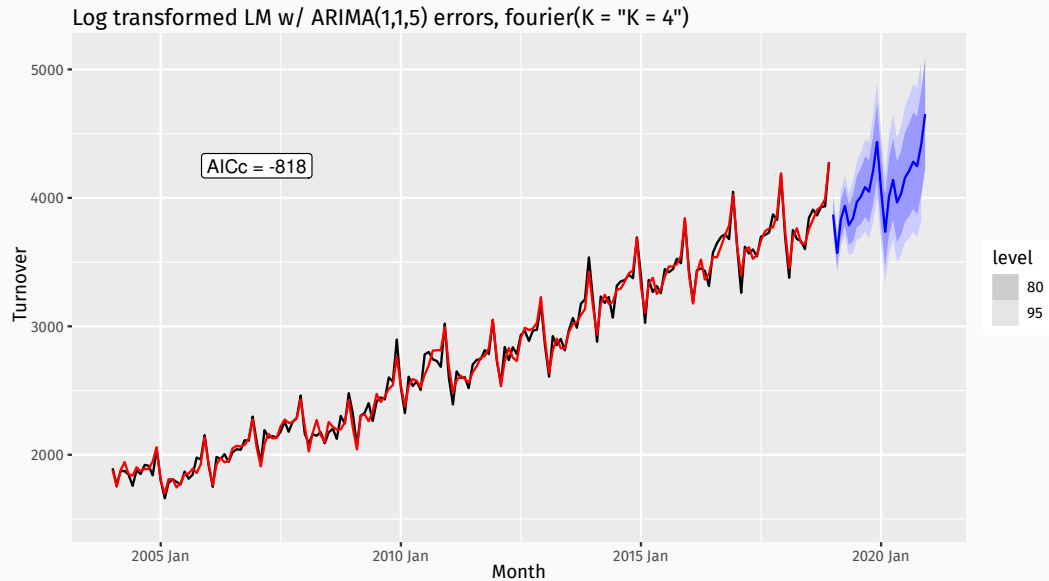


# Eating-out expenditure

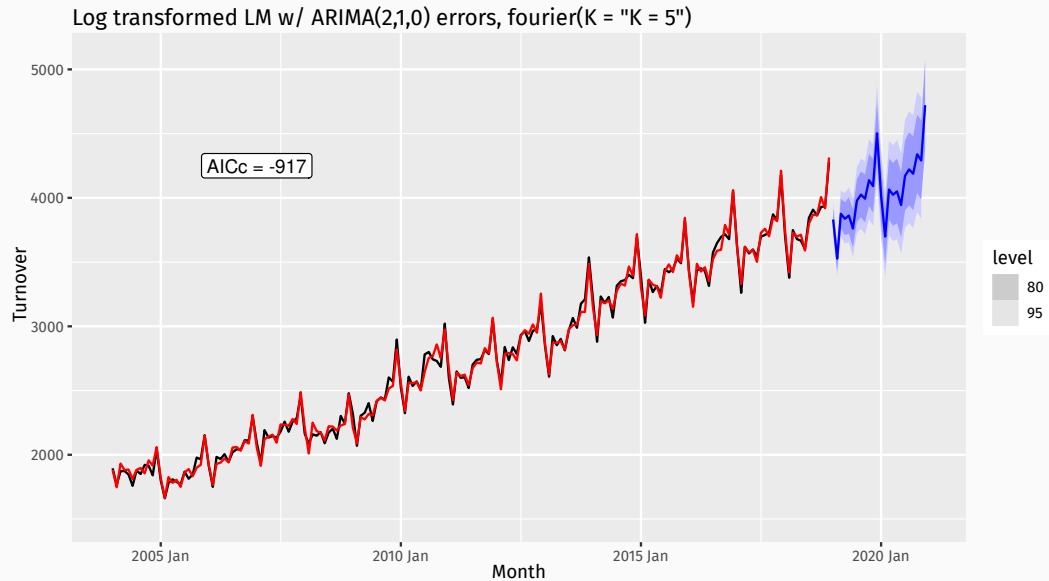




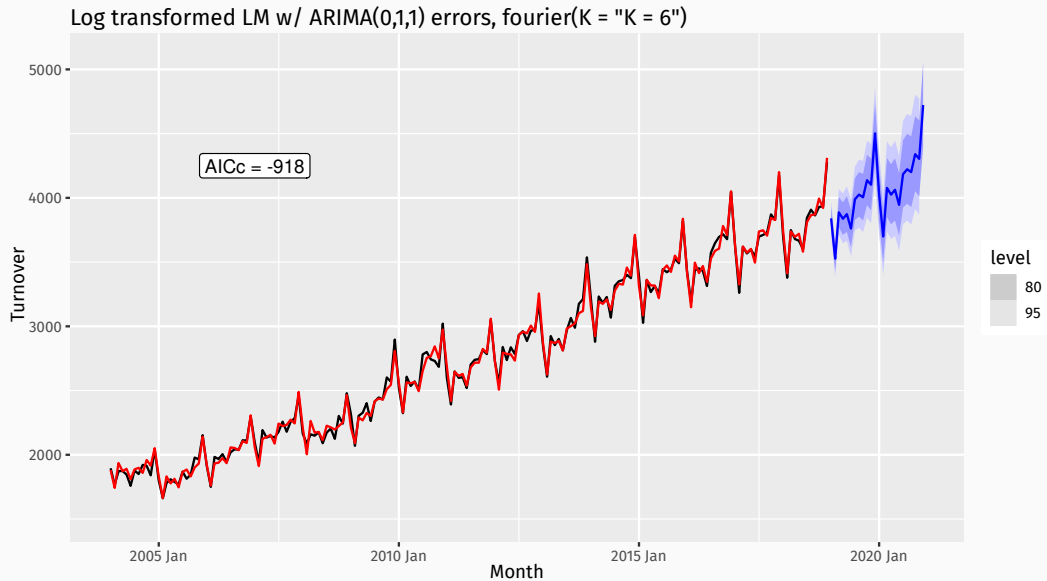
# Eating-out expenditure



# Eating-out expenditure



# Eating-out expenditure



# Example: weekly gasoline products

```
fit <- us_gasoline |> model(ARIMA(Barrels ~ fourier(K = 13) + PDQ(0, 0, 0)))  
report(fit)
```

Series: Barrels

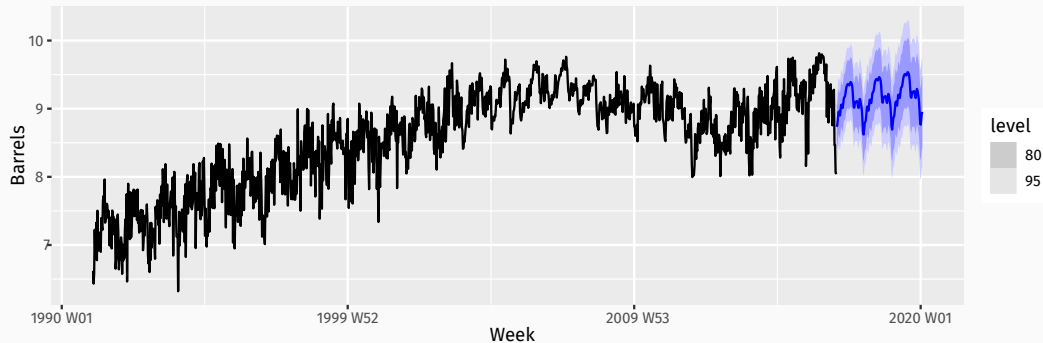
Model: LM w/ ARIMA(0,1,1) errors

Coefficients:

	ma1	fourier(K = 13)C1_52	fourier(K = 13)S1_52
	-0.8934	-0.1121	-0.2300
s.e.	0.0132	0.0123	0.0122
	fourier(K = 13)C2_52	fourier(K = 13)S2_52	
	0.0420	0.0317	
s.e.	0.0099	0.0099	
	fourier(K = 13)C3_52	fourier(K = 13)S3_52	
	0.0832	0.0346	
s.e.	0.0094	0.0094	
	fourier(K = 13)C4_52	fourier(K = 13)S4_52	
	0.0185	0.0398	
s.e.	0.0092	0.0092	
	fourier(K = 13)C5_52	fourier(K = 13)S5_52	
	-0.0315	0.0009	
s.e.	0.0091	0.0091	
	fourier(K = 13)C6_52	fourier(K = 13)S6_52	

# Example: weekly gasoline products

```
forecast(fit, h = "3 years") |>  
  autoplot(us_gasoline)
```



# Outline

1 Regression with ARIMA errors

2 Lab Session 18

3 Dynamic harmonic regression

4 Lab Session 19

5 Lagged predictors

## Lab Session 19

Repeat Lab Session 18 but using all available data, and handling the annual seasonality using Fourier terms.

# Outline

1 Regression with ARIMA errors

2 Lab Session 18

3 Dynamic harmonic regression

4 Lab Session 19

5 Lagged predictors



# Lagged predictors

Sometimes a change in  $x_t$  does not affect  $y_t$  instantaneously

- $y_t$  = sales,  $x_t$  = advertising.
- $y_t$  = stream flow,  $x_t$  = rainfall.
- $y_t$  = size of herd,  $x_t$  = breeding stock.

# Lagged predictors

Sometimes a change in  $x_t$  does not affect  $y_t$  instantaneously

- $y_t$  = sales,  $x_t$  = advertising.
  - $y_t$  = stream flow,  $x_t$  = rainfall.
  - $y_t$  = size of herd,  $x_t$  = breeding stock.
- 
- These are dynamic systems with input ( $x_t$ ) and output ( $y_t$ ).
  - $x_t$  is often a leading indicator.
  - There can be multiple predictors.

# Lagged predictors

The model include present and past values of predictor:

$X_t, X_{t-1}, X_{t-2}, \dots$

$$y_t = a + \nu_0 X_t + \nu_1 X_{t-1} + \dots + \nu_k X_{t-k} + \eta_t$$

where  $\eta_t$  is an ARIMA process.

# Lagged predictors

The model include present and past values of predictor:

$X_t, X_{t-1}, X_{t-2}, \dots$

$$y_t = a + \nu_0 X_t + \nu_1 X_{t-1} + \dots + \nu_k X_{t-k} + \eta_t$$

where  $\eta_t$  is an ARIMA process.

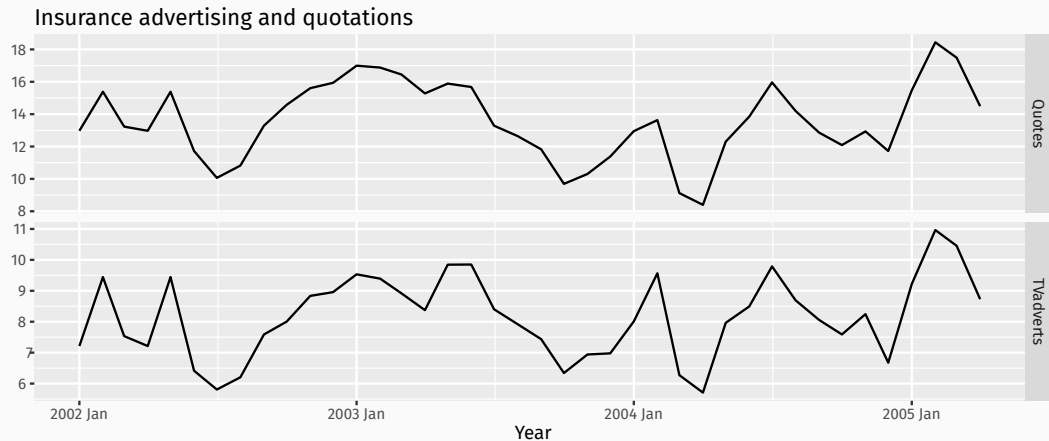
- $x$  can influence  $y$ , but  $y$  is not allowed to influence  $x$ .

# Example: Insurance quotes and TV adverts

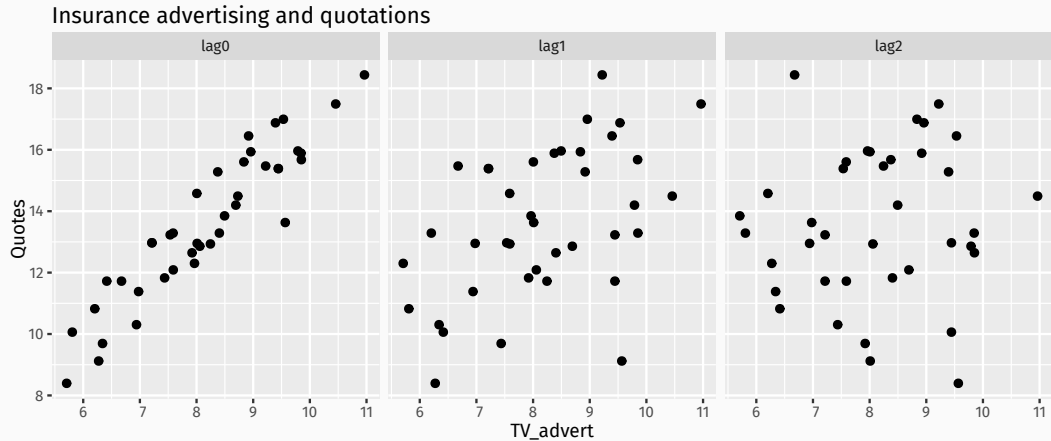
```
insurance
```

```
# A tsibble: 40 x 3 [1M]
      Month Quotes TVadverts
    <mth>   <dbl>    <dbl>
1 2002 Jan   13.0     7.21
2 2002 Feb   15.4     9.44
3 2002 Mar   13.2     7.53
4 2002 Apr   13.0     7.21
5 2002 May   15.4     9.44
6 2002 Jun   11.7     6.42
7 2002 Jul   10.1     5.81
8 2002 Aug   10.8     6.20
9 2002 Sep   13.3     7.59
10 2002 Oct   14.6     8.00
# i 30 more rows
```

# Example: Insurance quotes and TV adverts



# Example: Insurance quotes and TV adverts



# Example: Insurance quotes and TV adverts

```
fit <- insurance |>
  # Restrict data so models use same fitting period
  mutate(Quotes = c(NA, NA, NA, Quotes[4:40])) |>
  model(
    ARIMA(Quotes ~ pdq(d = 0) + TVadverts),
    ARIMA(Quotes ~ pdq(d = 0) + TVadverts +
      lag(TVadverts)),
    ARIMA(Quotes ~ pdq(d = 0) + TVadverts +
      lag(TVadverts) +
      lag(TVadverts, 2))),
    ARIMA(Quotes ~ pdq(d = 0) + TVadverts +
      lag(TVadverts) +
      lag(TVadverts, 2) +
      lag(TVadverts, 3))
  )
```



# Example: Insurance quotes and TV adverts

```
glance(fit)
```

Lag order	sigma2	log_lik	AIC	AICc	BIC
0	0.265	-28.3	66.6	68.3	75.0
1	0.209	-24.0	58.1	59.9	66.5
2	0.215	-24.0	60.0	62.6	70.2
3	0.206	-22.2	60.3	65.0	73.8

# Example: Insurance quotes and TV adverts

```
# Re-fit to all data
fit <- insurance |>
  model(ARIMA(Quotes ~ TVadverts + lag(TVadverts) + pdq(d = 0)))
report(fit)
```

Series: Quotes

Model: LM w/ ARIMA(1,0,2) errors

Coefficients:

	ar1	ma1	ma2	TVadverts	lag(TVadverts)	intercept
	0.512	0.917	0.459	1.2527	0.1464	2.16
s.e.	0.185	0.205	0.190	0.0588	0.0531	0.86

sigma^2 estimated as 0.2166: log likelihood=-23.9

AIC=61.9 AICc=65.4 BIC=73.7

# Example: Insurance quotes and TV adverts

```
# Re-fit to all data
fit <- insurance |>
  model(ARIMA(Quotes ~ TVadverts + lag(TVadverts) + pdq(d = 0)))
report(fit)
```

Series: Quotes

Model: LM w/ ARIMA(1,0,2) errors

Coefficients:

	ar1	ma1	ma2	TVadverts	lag(TVadverts)	intercept
	0.512	0.917	0.459	1.2527	0.1464	2.16
s.e.	0.185	0.205	0.190	0.0588	0.0531	0.86

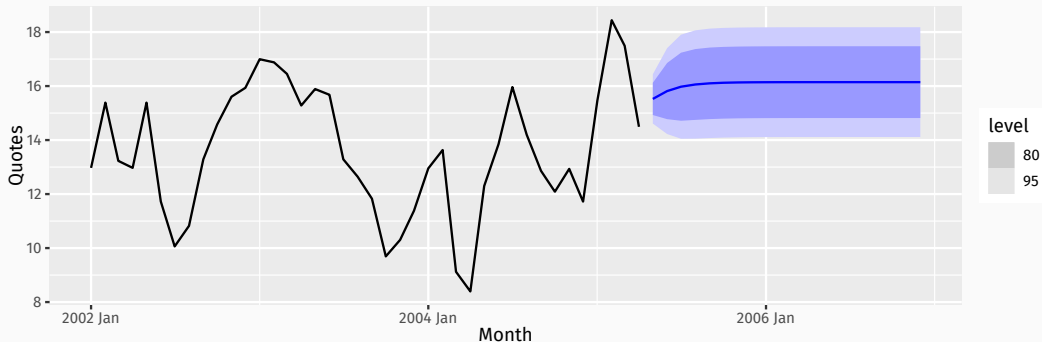
sigma^2 estimated as 0.2166: log likelihood=-23.9

AIC=61.9 AICc=65.4 BIC=73.7

$$y_t = 2.16 + 1.25x_t + 0.15x_{t-1} + \eta_t,$$
$$\eta_t = 0.512\eta_{t-1} + \varepsilon_t + 0.92\varepsilon_{t-1} + 0.46\varepsilon_{t-2}.$$

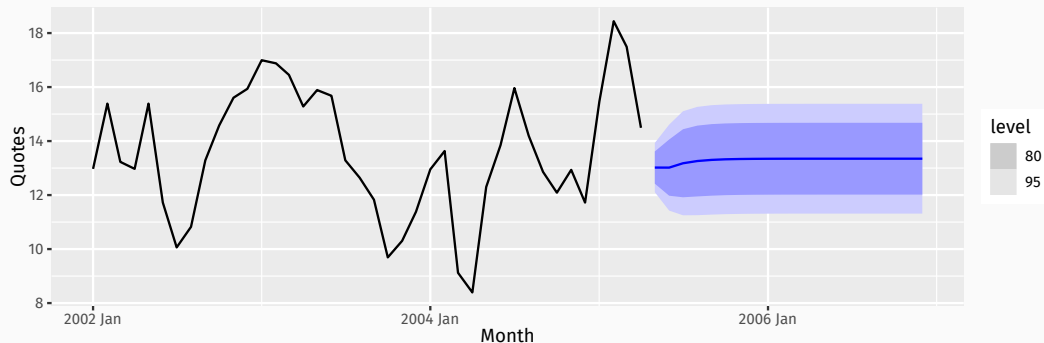
# Example: Insurance quotes and TV adverts

```
advert_a <- new_data(insurance, 20) |>  
  mutate(TVadverts = 10)  
forecast(fit, advert_a) |> autoplot(insurance)
```



# Example: Insurance quotes and TV adverts

```
advert_b <- new_data(insurance, 20) |>  
  mutate(TVadverts = 8)  
forecast(fit, advert_b) |> autoplot(insurance)
```



# Example: Insurance quotes and TV adverts

```
advert_c <- new_data(insurance, 20) |>  
  mutate(TVadverts = 6)  
forecast(fit, advert_c) |> autoplot(insurance)
```

