# Class 4b: Simple Linear Regression diagnostics

**Business Forecasting** 

# Roadmap

## This class

- Testing assumptions behind residuals
  - Linearity
  - Constant Variance
  - Uncorrelated Residuals
  - Normality

### Let's revisit the assumptions behind linear model:

- 1. Model is linear in the parameter and with additive error term
- 2.  $E(u_i) = 0$
- 3.  $Var(u_i) = \sigma^2$
- 4.  $cov(u_i, u_j) = 0$

Additional assumption needed for hypothesis testing and confidence intervals:

1. 
$$u_i \sim N(0,\sigma)$$

# **Assumptions**

Visualizing residuals, we can test:

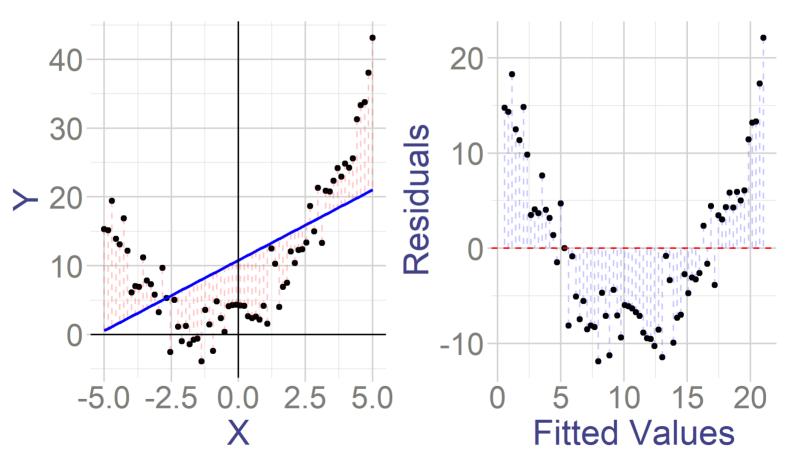
- Linearity
- Constant Variance (homoskedasticity)
- Uncorrelated errors

With vizuale and numerical tests we can analyze:

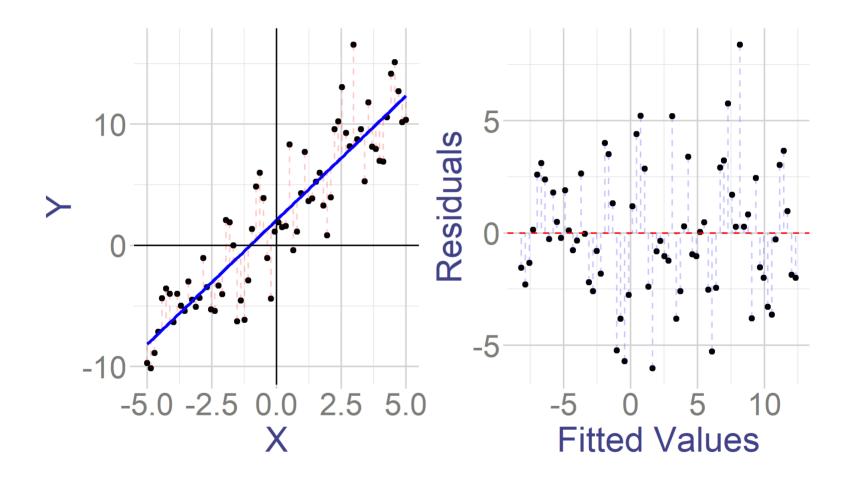
• Normality

# **Linearity diagnostic**

- 1. Plot residuals against fitted values of y  $\hat{y}$
- 2. Check if residuals have systematic non-linear pattern

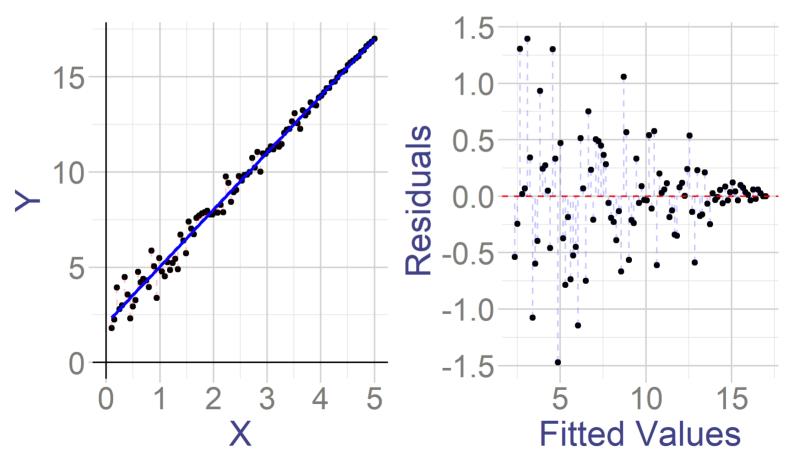


# **Linearity diagnostic**

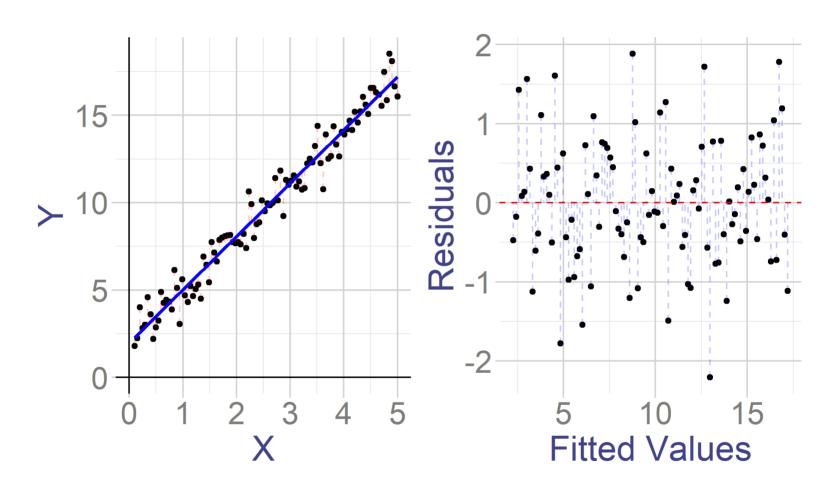


# Constant variance (homoskedasticity) diagnostic

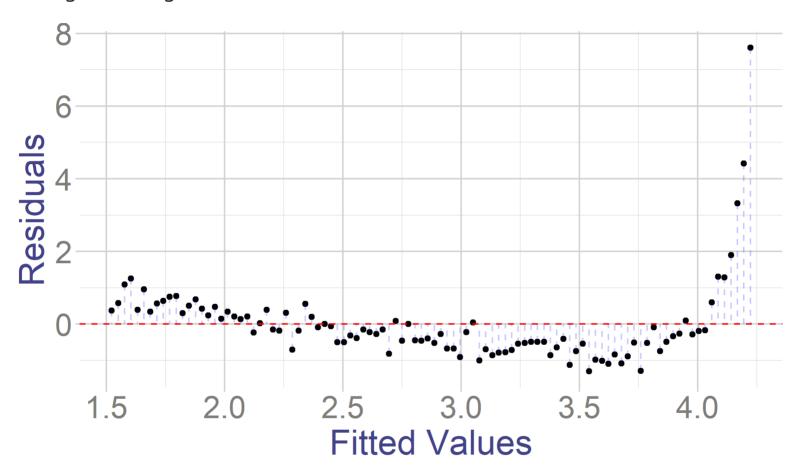
- 1. Plot residuals against fitted values of y  $\hat{y}$
- 2. Check if variance changes as  $\hat{y}$  changes (heteroskedasticity)



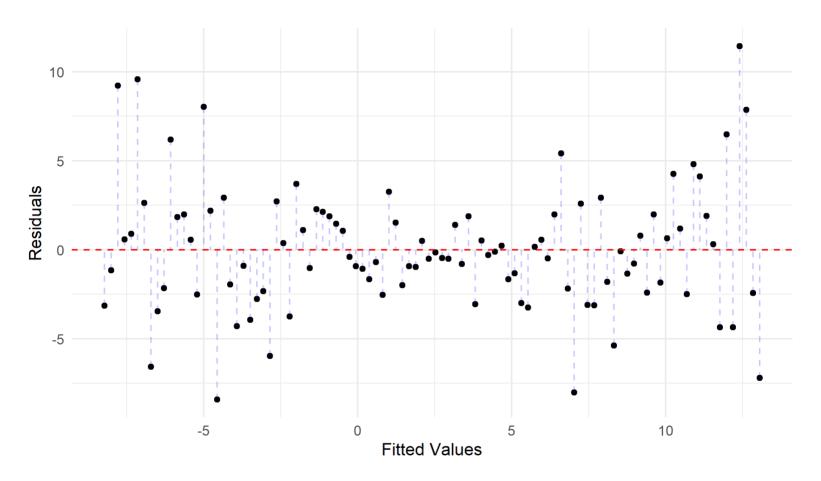
# Constant variance (homoskedasticity) diagnostic



## What goes wrong here?

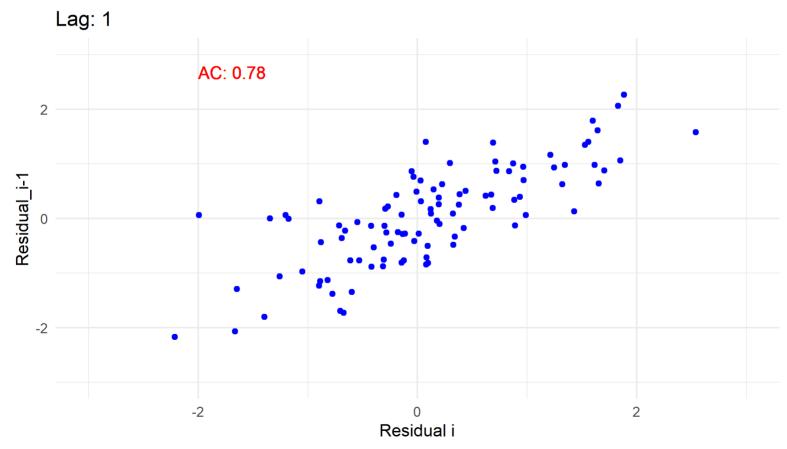


## What goes wrong here?



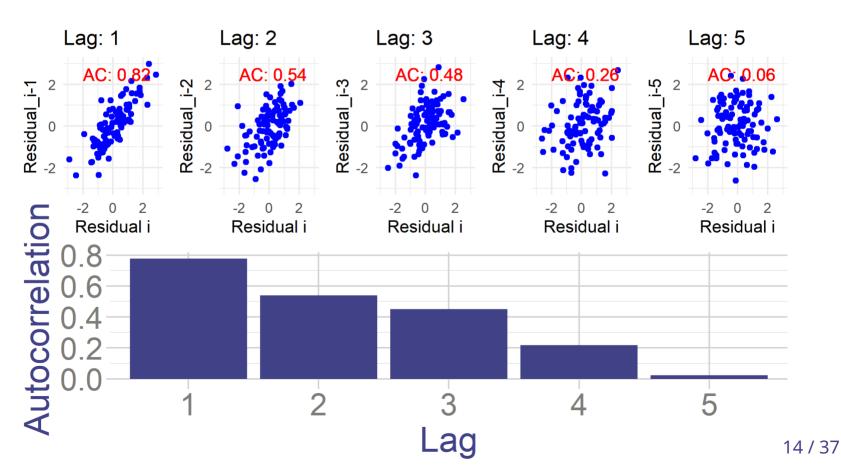
## Correlation of error terms

- 1. Plot fitted residuals vs their value in previous observation  $e_i$  vs  $e_{i-1}$
- 2. So  $e_2$  vs  $e_1$ ,  $e_5$  vs  $e_4$  etc



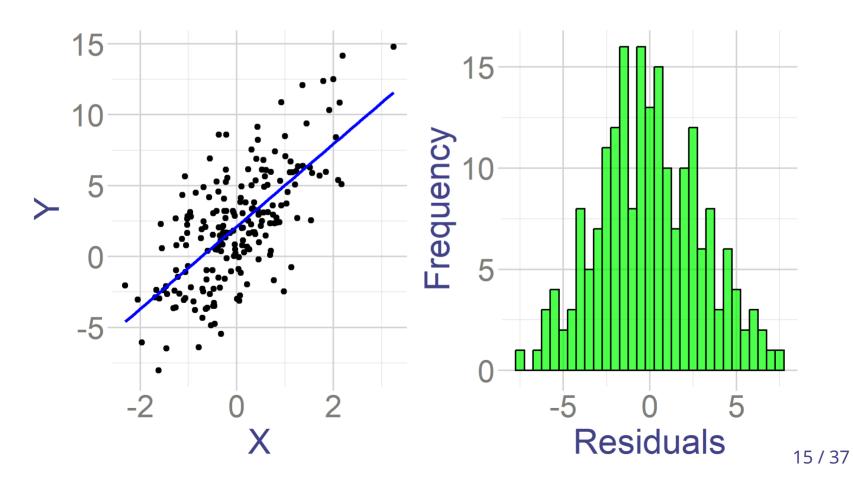
## Correlation of error terms

- 1. We can also calculate the correlation with other lags
  - $\circ$  Example:  $e_i$  vs  $e_{i-3}$
  - $\circ$  Note down correlation at each lag:  $ho(e_i,e_{i-1})$ ,  $ho(e_i,e_{i-2})$ ,  $ho(e_i,e_{i-3})$



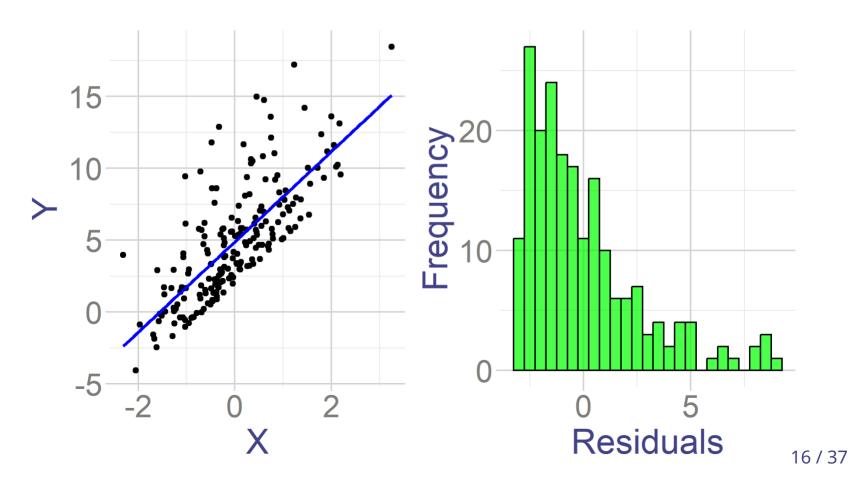
We can start by looking at histograms

• Some are obvious



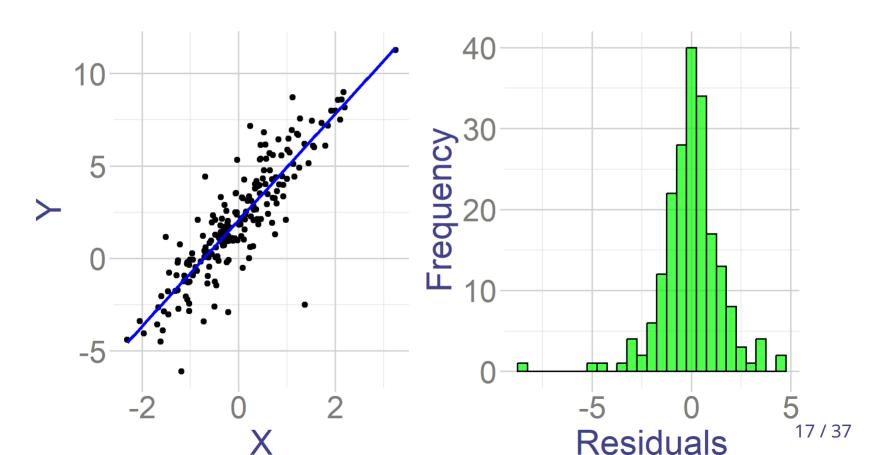
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We can start by looking at histograms

- Some are **NOT** obvious
- Then we need a different test

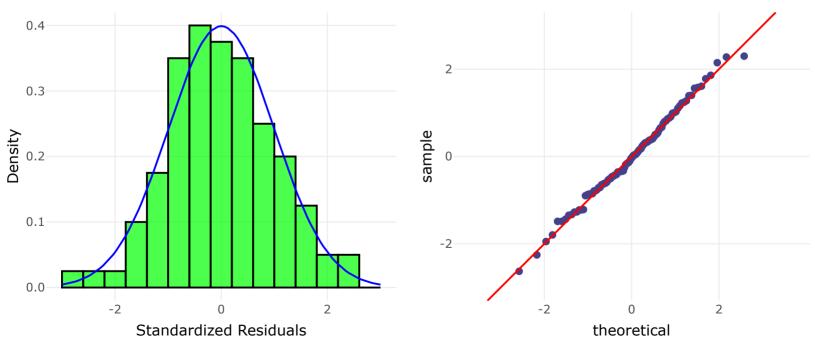


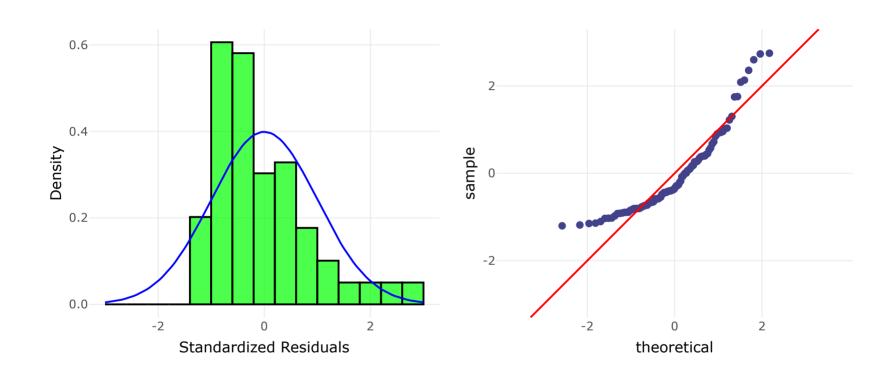
#### **Q-Q Plot**: Quantlie-Quantile Plot

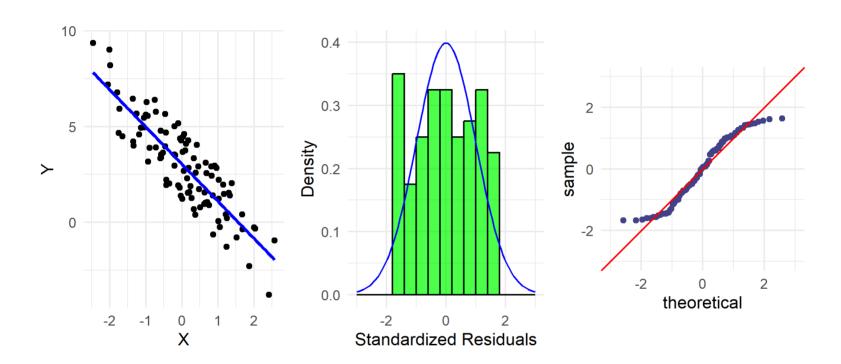
- Comparing quantiles of our data to what they should be if they come from normal distribution
- Procedure:
  - Standardize residuals
  - Sort them
  - Check which quantile they represent
  - $\circ$  This is equivalent to checking cumulative probability:  $CP_i = rac{Index}{n+1}$
  - Where index is the number of observation if we sort if from smallest to largest
    - 1 is the smallest, 2 is the second smallest, ..., n is the largest
  - o In other words, what share of data is smaller than this observation
  - Compare them to quantiles from standard normal
  - If our distribution is normal, the quantiles should be similar

Show 10   ✓ ent	ries			
Residuals 🛊	Standardized_Residuals 崇	Index 🍦	Cumulative_Probability 🝦	Quantile_Normal 🝦
-1.681	-0.713	23	0.228	-0.745
-0.691	-0.351	39	0.386	-0.29
4.676	1.609	95	0.941	1.563
0.212	-0.022	51	0.505	0.013
0.388	0.043	54	0.535	0.088
5.145	1.78	96	0.95	1.645
1.383	0.406	69	0.683	0.476
-3.795	-1.485	5.5	0.054	-1.607
-2.061	-0.852	19	0.188	-0.885
-1.337	-0.587	29	0.287	-0.562
Showing 1 to 10 of 100 entries			Previous 1 2 3 4	5 10 Next

- Next, we plot the sample quantiles vs the standard normal quantiles
- If they are similar, they should be on the straight line





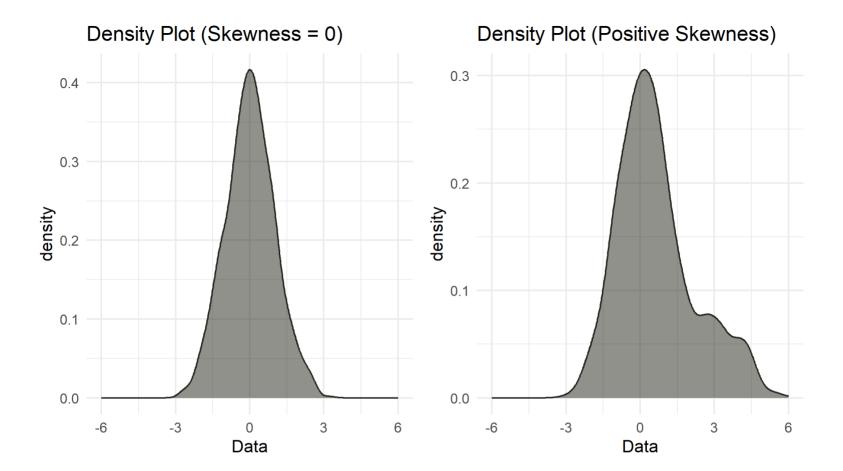


 We can also use the Jarque-Bera Test to see whether sample comes from a normal distribution

#### Intuition

• Skeweness of normal distribution is 0 (it's symmetric)

$$S = rac{rac{1}{n} \sum_{i=1}^{n} (x_i - ar{x})^3}{\left(rac{1}{n} \sum_{i=1}^{n} (x_i - ar{x})^2
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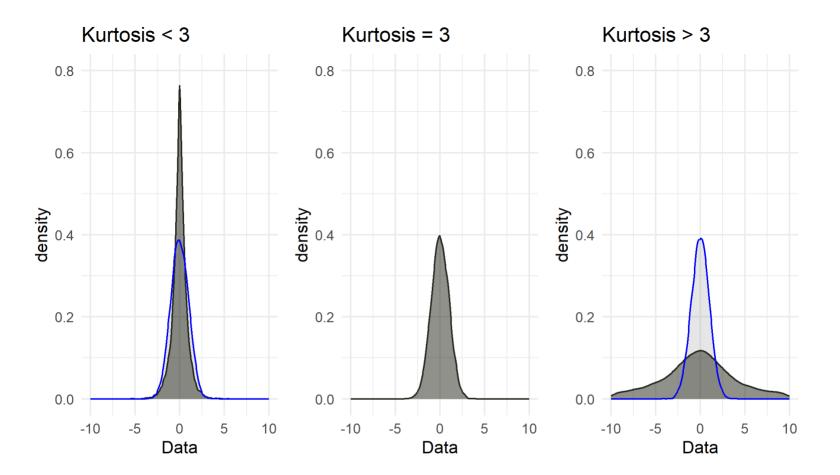
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- Kurtosis of normal distribution is 3
- Excess kurtosis is 0

$$EK = rac{rac{1}{n} \sum_{i=1}^{n} (x_i - ar{x})^4}{\left(rac{1}{n} \sum_{i=1}^{n} (x_i - ar{x})^2
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- We will test, whether our sample has (more or less)
  - Skewenss of 0
  - Kurtosis of 3

The test statistic for our test is:

$$JB=rac{n}{6}igg(rac{S^2}{2}+rac{EK^2}{4}igg)$$

- Its value will be high if:
  - Skeweness deviates significantly from 0
  - Kurtosis deviates significantly from 3
- If the data really comes from normal (that's our null hypothesis), then:

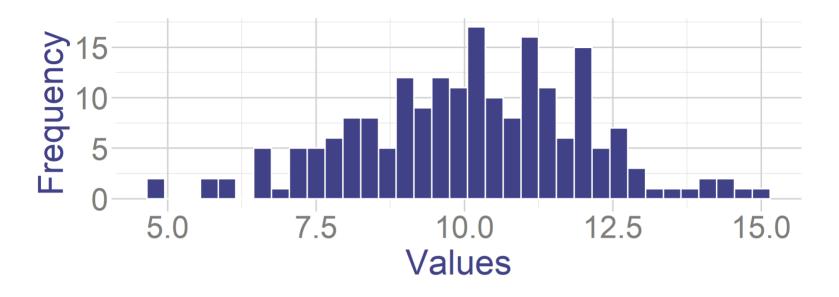
$$JB\sim\chi_2$$

• It follows the Chi-squared distribution with 2 degrees of freedom.

So in our usual testing setting:

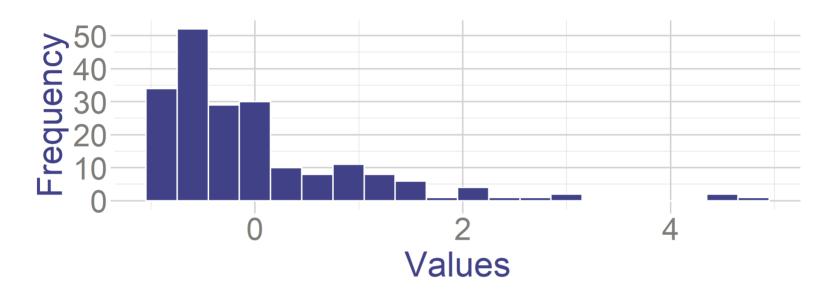
- $H_0:e_i$  comes from normal (JB is small)
- $H_A:e_i$  Does not come from normal (JB is large)
- It's a one sided test, so we reject at  $\alpha$  if

$$JB_{test} > \chi_{1-\alpha,2}$$



```
library(tseries)
jarque.bera.test(sample_data)
```

```
##
## Jarque Bera Test
##
## data: sample_data
## X-squared = 0.96619, df = 2, p-value = 0.6169
```



```
library(tseries)
jarque.bera.test(sample_data)
```

```
##
## Jarque Bera Test
##
## data: sample_data
## X-squared = 420.19, df = 2, p-value < 2.2e-16</pre>
```