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Logarithms

Logarithms allow us to move between multiplicative equations and additive ones.

Logs are defined relative to a base number. If we take 10 as the base then  $y = log_{10}(x)$  means  $10^x = y$ .

It's easy to calculate the log of powers of 10:

log(10) = 1	$10^1 = 10$
log(100) = 2	$10^2 = 100$
log(1000) = 3	$10^3 = 1000$
$\log(100000) = 6$	$10^6 = 1000000$

 $10^0$  is defined as 1, so the log of 1 is zero.



For numbers between 1 and 0, logs are negative

$$\begin{array}{ll} \frac{1}{10} = 10^{-1} & \log(0.1) = -1 \\ \frac{1}{100} = 10^{-2} & \log(0.01) = -2 \\ \frac{1}{1000} = 10^{-3} & \log(0.001) = -3 \end{array}$$

The  $\log_{10}$  of powers of 10 are integers, but we can raise 10 to non-integer powers too, to get the log of any number greater than zero. For instance,  $10^{2.09}$  is 123, so the log of 123 is 2.09.



We can see with round powers of 10 than using logs we can move between multiplication and addition:

 $100 \times 1000 = 100000$ 

 $10^2 \times 10^3 = 10^5 = 10^{2+3}$ 



Thus do calculate A × B we do as follows:

- Calculate log(A)
- Calclate log(B)
- Calculate log(C) = log(A) + log(B)
- Take the anti-log of log(C), i.e.,  $10^{log(C)} = C$



```
Multiply 12345 by 67890
log(12345) = 9.421
log(67890) = 11.126
9.421 + 11.126 = 20.547
10^{20.547} = 838102050
```



If you have a certain quantity (e.g., money in a bank account), whose value increases by a constant proportion every year, its value in any year depends on a multiplicative relationship.

Let's say the increases is  $\alpha$  (i.e., a 10% increase means  $\alpha$  = 1.1)



Year 0	100
Year 1	100 × $\alpha$
Year 2	100 × $\alpha$ × $\alpha$
Year 3	100 × $\alpha$ × $\alpha$ × $\alpha$
Year 4	100 × $\alpha$ × $\alpha$ × $\alpha$ × $\alpha$
Year 5	$100 \times \alpha \times \alpha \times \alpha \times \alpha \times \alpha$

In short, the value in year t is  $100 \times \alpha^t$ 

$$y_t = 100 \times \alpha^t$$



#### **Constant proportional increase**

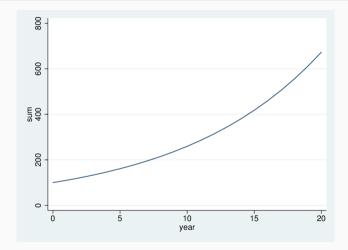


Figure 1: A constant proportional increase



#### But if we convert to logs we can calculate it as follows

$$log(y_t) = log(100) + t \times log(\alpha)$$

In other words, rather than multiplying by  $\alpha$  every year, we add log( $\alpha$ ).



#### Plot

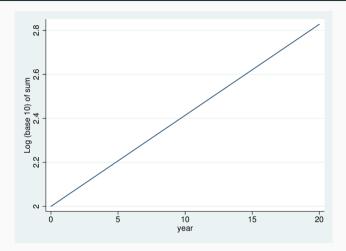


Figure 2: Taking the base-10 log of the sum: a straight line

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This gives a straight line relationship (see Fig 2).

Thus we can use logs to move between multiplicative and additive (straight-line) relationships.



Logs to the base 10 are easy to understand, but the base number need not be 10. A log to the base n is defined thus:

$$y = log_n(x) \Leftrightarrow n^y = x$$



Computer scientists often use  $\log_2$ , but the most common log base is the special number  $e \approx 2.7183$ . This has some special mathematical properties that make certain calculations easier.

Logs to base e are called natural logs, often written ln(x) etc:

$$y = ln(x) \Leftrightarrow e^y = x$$

See Fig 3, which shows that the natural log also gives a straight line.



#### Natural log straight line

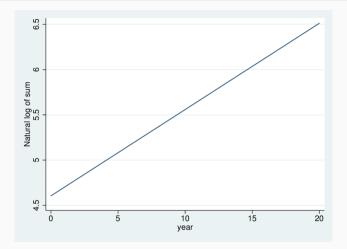


Figure 3: Taking the natural log of the sum: also a straight line



- Fig 4 shows the natural log of X from 0.1 (-2.303) to 100 (4.605).
- For X = 1, the log is 0.
- As X approaches 0, the log falls faster and faster.
- As X rises above 1, the log rises, but more slowly as it goes.
- Note that the log rises from X = 5 to 10 as much as it does from X = 40 to 80.



# X vs In(X)

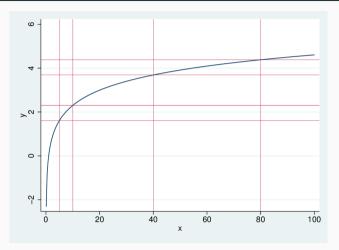


Figure 4: The natural log of X for X from 0.1 to 100



Early pandemic: exponential curves

- In the early stage of an epidemic, infections tend to increase at a steady rate
- On average each infected person infects others at a given rate, e.g., one person every four days
- · So numbers of cases tend to rise at a steady percentage
  - · New infections are proportional to existing infections
  - 100 today means 125 tomorrow, 156 the next day, etc.



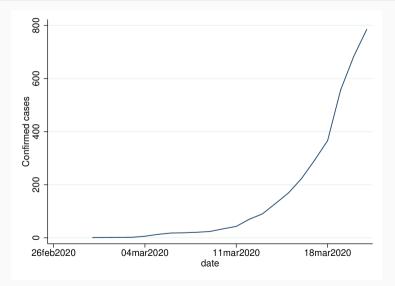
If we look at the raw number of cases in Ireland:

- it starts off very low
- · stays there for a while
- · but then starts rising
- · and rising faster and faster

line cases date



#### **Confirmed cases in Ireland**





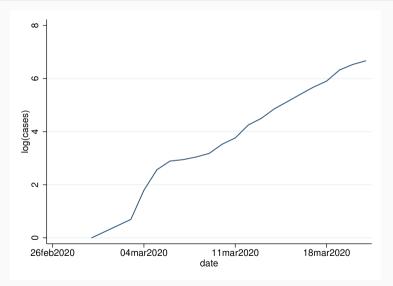
If we plot the log of the cases we see a different picture

- · wobbly to begin with
- · then approximating a straight line

gen lcases = log(cases)
line lcases date



#### Log cases





- A straight line in logs means log(ncases) increases by more or less a set amount very day
- That means neases rises by a set proportion every day: exponential rise
- Exponential: even if it starts small, if given long enough, will get very very big!



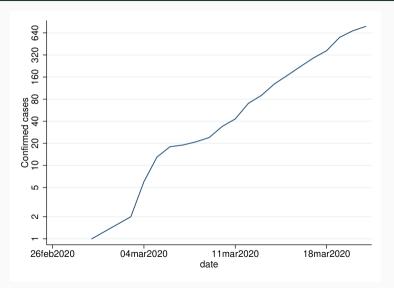
#### We can graph log(cases) but we can also graph cases with a Y log-scale

line cases date, yscale(log) ylabel(1 2 5 10 20 40 80 160 320 640)

This gives the advantages of the logging while retaining the real numbers on the axis



#### Log scale, real cases





#### Log-scale graphic in the wild

# Coronavirus deaths in Italy, Spain and the UK are increasing much more rapidly than they did in China



Source: FT analysis of Johns Hopkins University, CSSE; Worldometers. Data updated March 21, 19:00 GMT © FT

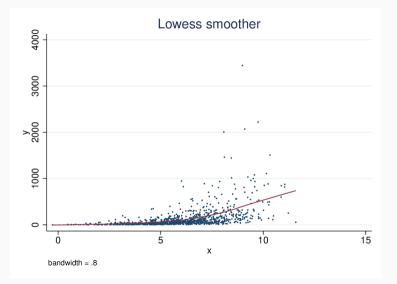


Log regression

- Where the underlying relationship is multiplicative, linear regression doesn't work well
- · Implies an additive increase where a multiplicative one is better
- If we take the log of the dependent variable:
  - · better estimates
  - · often cures heteroscedasticity



#### Simulation: Y increases 65% for X +1





## Linear regression



## Predictions

Y vs X 4000 . 3000 y 2000 · . 1000 0 15 10 Ò 5 х



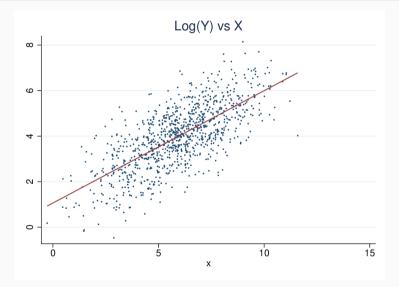




- + For a 1 unit change in X,  $log(\hat{Y})$  rises by 0.4933914
- Thus for a 1 unit change in X, Y rises by  $e^{0.4933914} = 1.638$
- $e^{0.4933914}$  is the antilog of 0.4933914



### Predictions





- Where the dependent variable is logged the prediction of the Y value is not simply the anti-log of the predicted log(Y)
- When we take the anti-log we must take account of the fact that residuals above the line expand by more than residuals below the line
- · Thus a small correction

$$log(Y) = a + bX$$
  
 $\hat{Y} = e^{log(Y)} * e^{\text{RMSE}^2/2}$ 

· where RMSE is the standard deviation of the regression

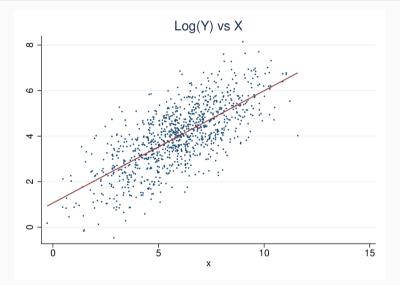




```
predict lyhat
gen elyh = exp(lyhat)
gen elyh2 = elyh * exp(rmse<sup>2</sup>/2)
```

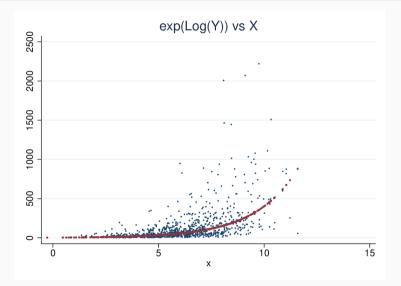
```
gen ly = log(y)
reg ly x
```

# Predictions: predict log(Y) on log scale



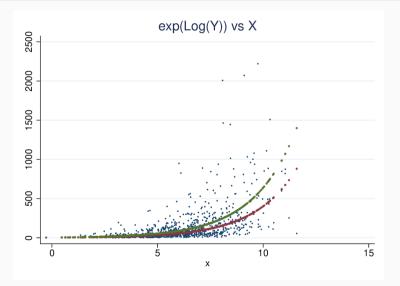


# Predictions: only $e^{log(Y)}$





#### Predictions: with correction





- We can apply log regression to the COVID-19 data
- A straight line on a log scale means a constant proportional increase.
- We can estimate this increase, regressing log(cases) on date.
- The slope, b, is the amount by which  $\log\hat{\mathrm{cases}}$  rises per day
- $e^b$  is then the multiplier by which cases rises per day

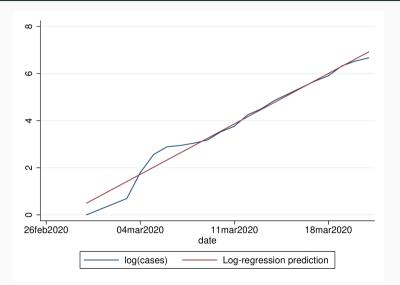
reg lcases date



## Stata output



## Logs with log regression





```
The log of cases rises by 0.3058 per day
This means cases rises by a factor of e^{0.3058} = 1.358
The increase is 1.358 - 1 = 0.358, or almost 36% per day
Implies a doubling about every 2.6 days
```



Exponential increase cannot go on indefinitely

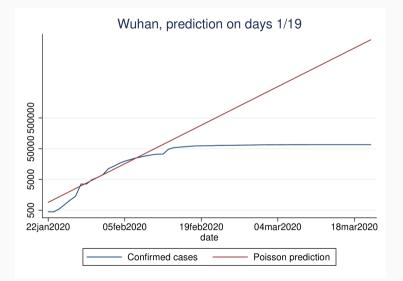
Even if nothing is done, the rate of increase will decline as fewer people are left unexposed

And interventions (isolation, tracing) will reduce the rate

See China, for example



#### Wuhan, with prediction based on 1st 19 days





If there is a constant rate of increase, logs give us straight lines

Graph the log, or use a log scale on the Y-axis

Log regression allows us to estimate the rate

Exponential increase isn't forever, but modelling the exponential helps us see where the rate starts to drop

Code available here: http://teaching.sociology.ul.ie/so5032/irecovid.do

