

Introduction to Econometrics, 5th edition

Chapter 2: Properties of the Regression Coefficients and Hypothesis Testing

True model

$$Y = \beta_1 + \beta_2 X + u$$

Fitted model

$$\hat{Y} = \hat{\beta}_1 + \hat{\beta}_2 X$$

$$\hat{\beta}_2 = \frac{(X_i - \bar{X})(Y_i - \bar{Y})}{(X_i - \bar{X})^2} = \beta_2 + (x_i - \bar{X})u_i$$

$$a_i = \frac{X_i - X}{\sum (X_j - \overline{X})^2}$$

In the previous slideshow, we saw that the error term is responsible for the variations of b_2 around its fixed component β_2 . We demonstrated mathematically that the expectation of the error term is zero and hence that is an unbiased estimator of β_2 .

True model

$$Y = \beta_1 + \beta_2 X + u$$

Fitted model

$$\hat{Y} = \hat{\beta}_1 + \hat{\beta}_2 X$$

$$\hat{\beta}_2 = \frac{(X_i - \overline{X})(Y_i - \overline{Y})}{(X_i - \overline{X})^2} = \beta_2 + (A_i u_i)$$

$$a_i = \frac{X_i - \overline{X}}{\sum (X_j - \overline{X})^2}$$

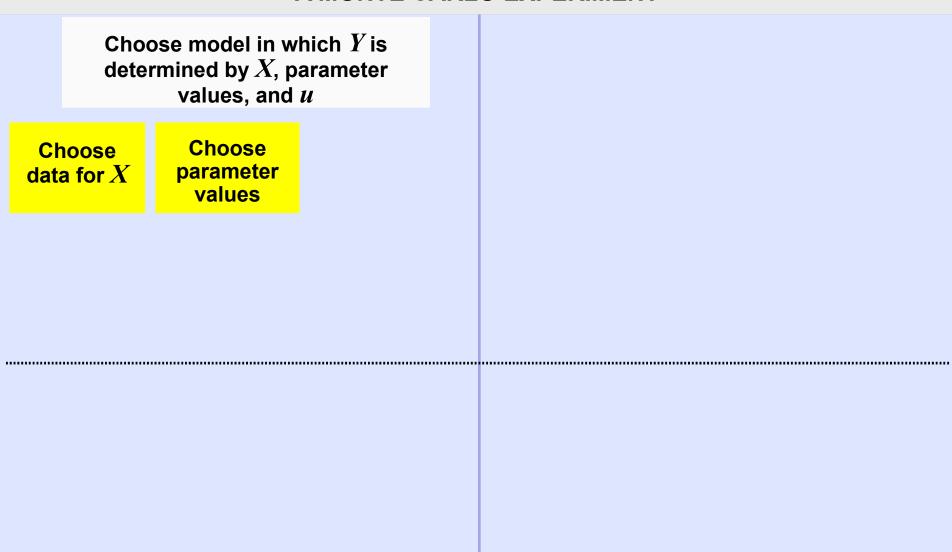
In this slideshow we will investigate the effect of the error term on $\hat{\beta}_2$ directly, using a Monte Carlo experiment (simulation).

Choose model in which Y is determined by X, parameter values, and *u*

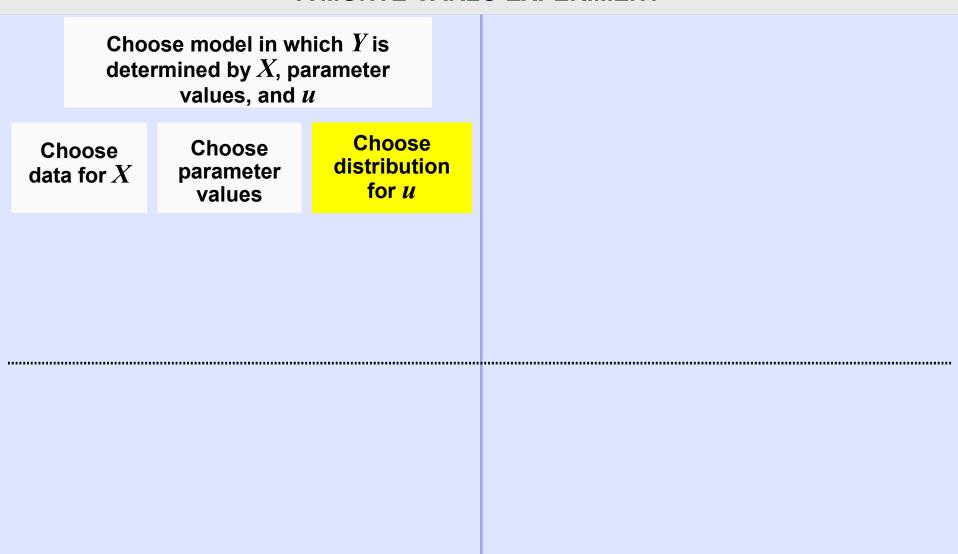
A Monte Carlo experiment is a laboratory-style exercise usually undertaken with the objective of evaluating the properties of regression estimators under controlled conditions.

Choose model in which Y is determined by X, parameter values, and *u*

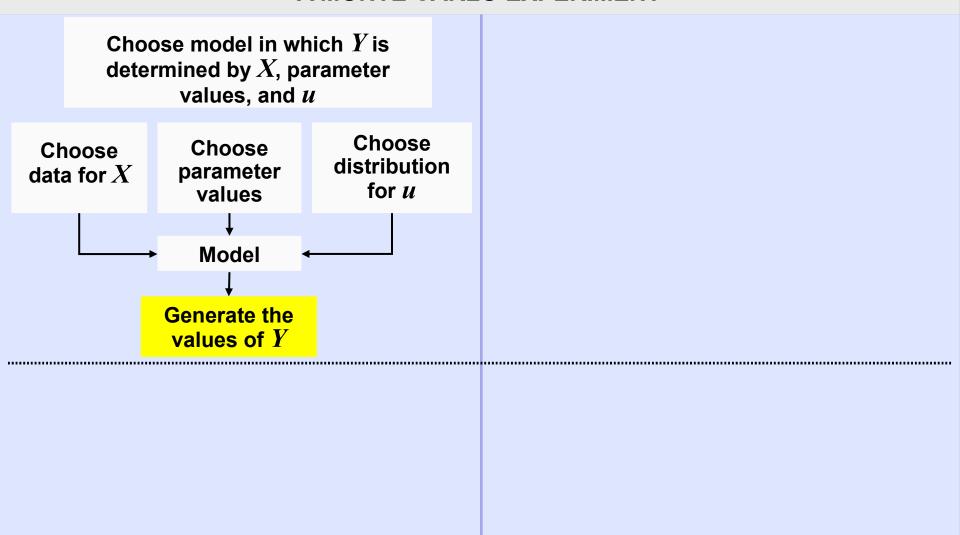
We will use one to investigate the behavior of OLS regression coefficients when applied to a simple regression model.



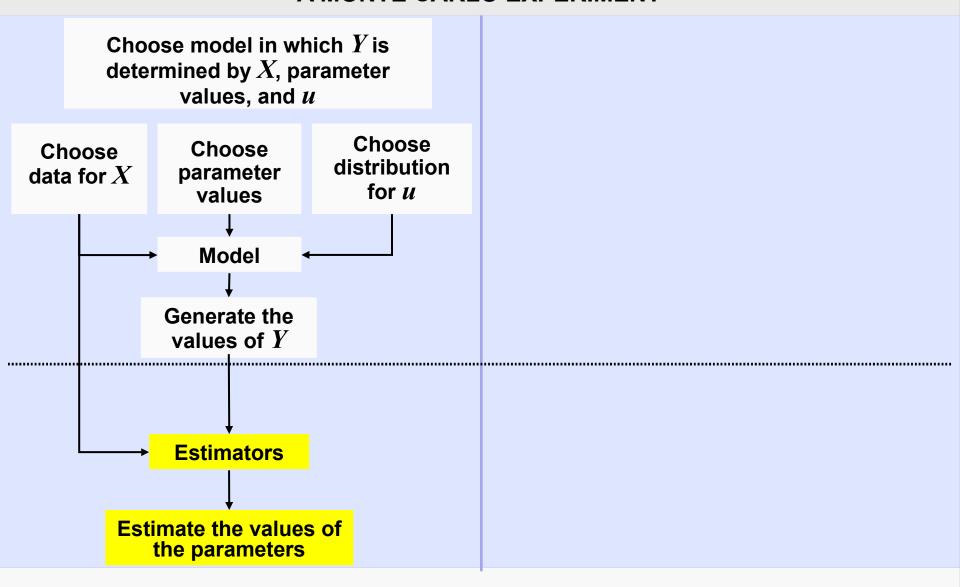
We will assume that Y is determined by a variable X and a disturbance term u, we will choose the data for X, and we will choose values for the parameters.



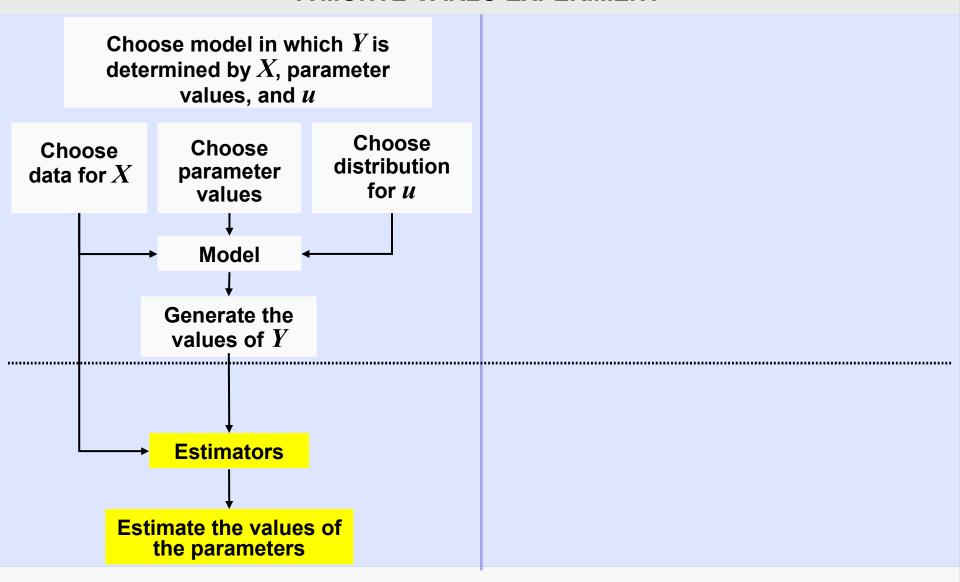
We will also generate values for the disturbance term randomly from a known distribution.



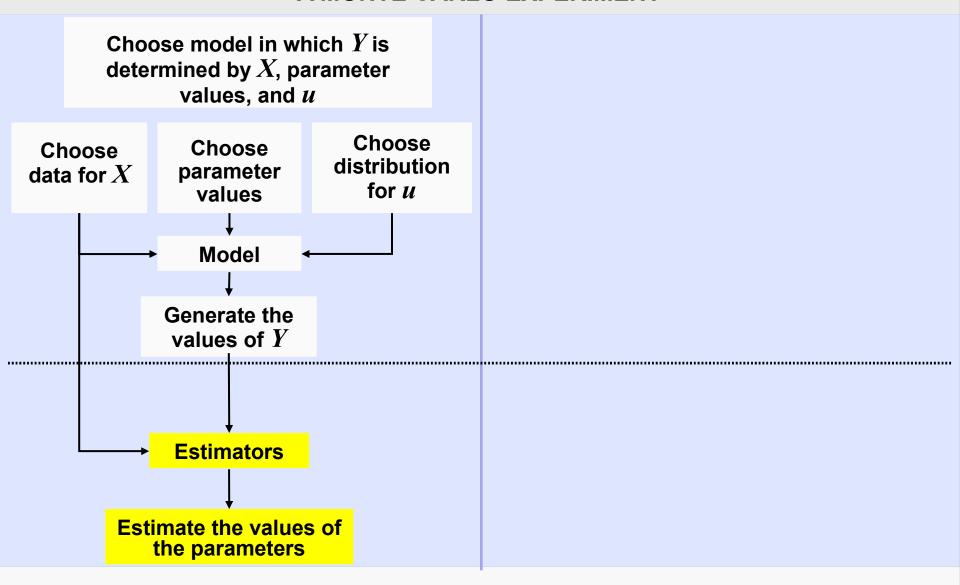
The values of Y in the sample will be determined by the values of X, the parameters and the values of the disturbance term.



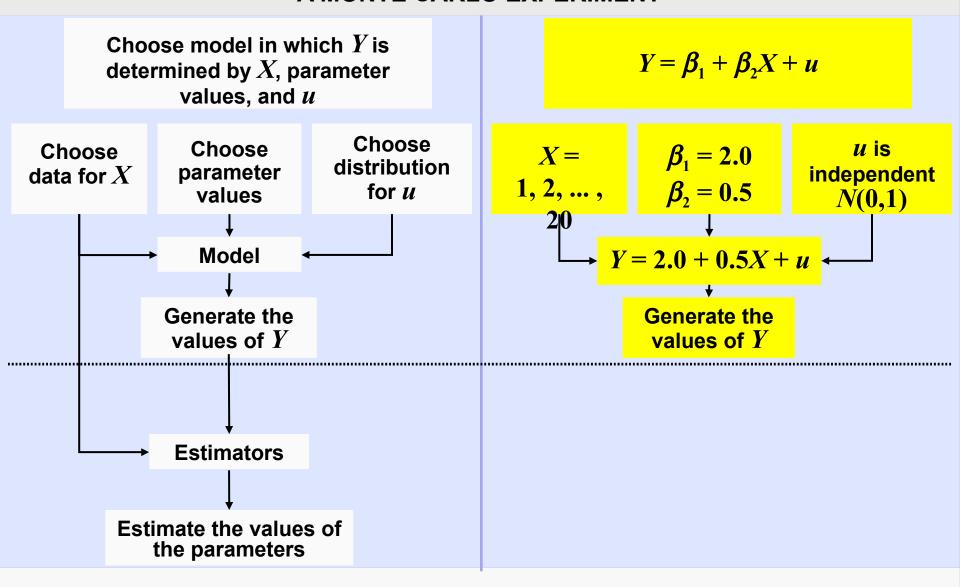
We will then use the regression technique to obtain estimates of the parameters using only the data on Y and X.



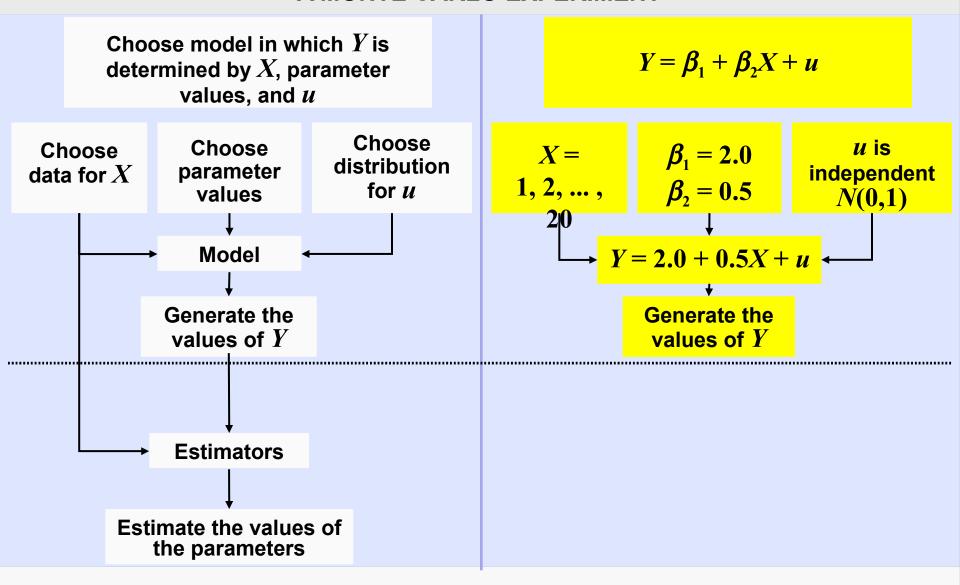
We can repeat the process indefinitely keeping the same data for X and the same values of the parameters but using new randomly-generated values for the disturbance term.



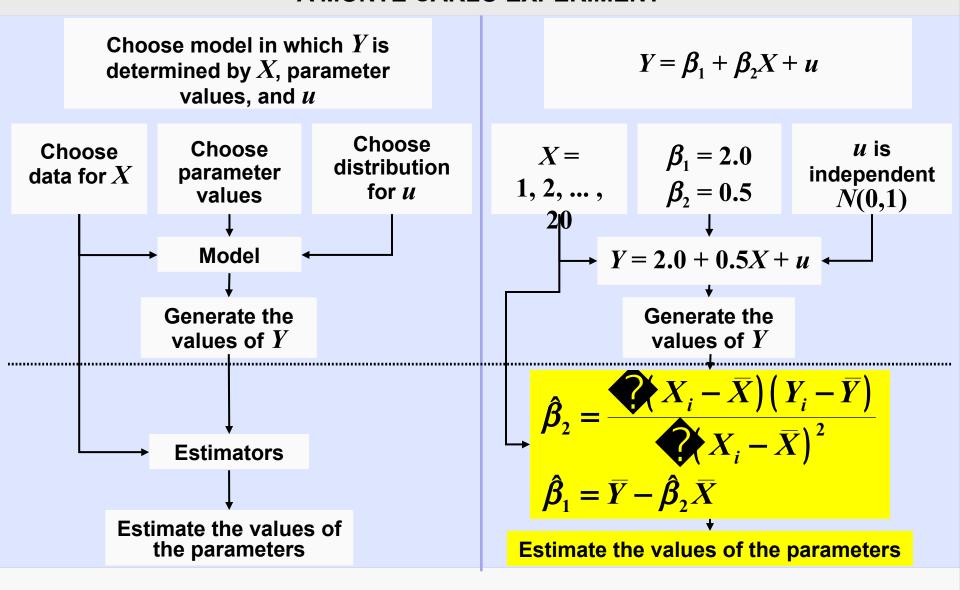
In this way we can derive probability distributions for the regression estimators which allow us, for example, to check up on whether they are biased or unbiased.



In this experiment we have 20 observations in the sample. X takes the values 1, 2, ..., 20. β_1 is equal to 2.0 and β_2 is equal to 0.5.



The disturbance term is generated randomly using a normal distribution with zero mean and unit variance. Hence we generate the values of *Y*.



We will then regress Y on X using the OLS estimation technique and see how well our estimates $\hat{\beta}_1$ and $\hat{\beta}_2$ correspond to the true values β_1 and β_2 .

$$Y = 2.0 + 0.5X + u$$

X	2.0+0.5 <i>X</i>	u	Υ		X	2.0+0.5 <i>X</i>	и	Y
1				ı	11			
2					12			
3				,	13			
4				•	14			
5				•	15			
6					16			
7					17			
8					18			
9					19			
10				2	20			

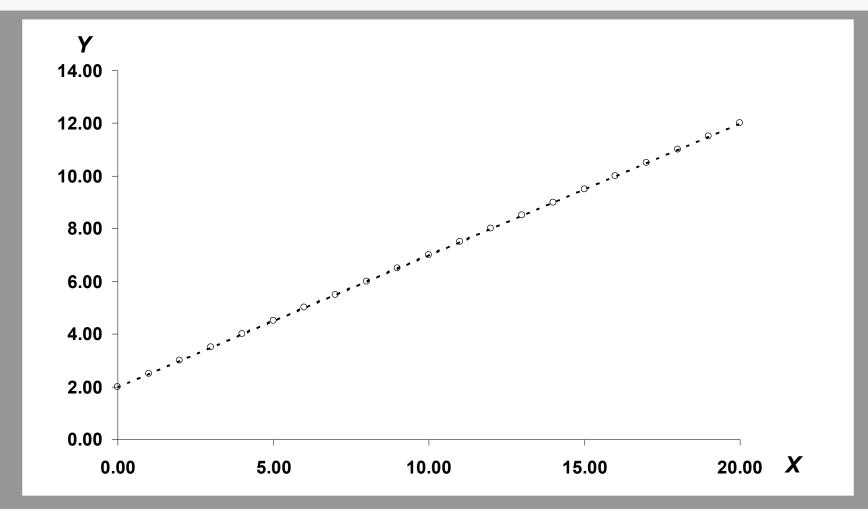
Here are the values of X, chosen quite arbitrarily.

$$Y = 2.0 + 0.5X + u$$

X	2.0+0.5 <i>X</i>	u	Υ	X	2.0+0.5 <i>X</i>	u	Y
1	2.5			11	7.5		
2	3.0			12	8.0		
3	3.5			13	8.5		
4	4.0			14	9.0		
5	4.5			15	9.5		
6	5.0			16	10.0		
7	5.5			17	10.5		
8	6.0			18	11.0		
9	6.5			19	11.5		
10	7.0			20	12.0		

Given our choice of numbers for β_1 and β_2 , we can derive the nonstochastic component of Y.

$$Y = 2.0 + 0.5X + u$$



The nonstochastic component is displayed graphically.

$$Y = 2.0 + 0.5X + u$$

X	2.0+0.5	X u	Y	X	2.0+0.5	X u	Y
1	2.5	-0.59		11	7.5	1.59	
2	3.0	-0.24		12	8.0	-0.92	
3	3.5	- 0.83		13	8.5	-0.71	
4	4.0	0.03		14	9.0	-0.25	
5	4.5	-0.38		15	9.5	1.69	
6	5.0	-2 .19		16	10.0	0.15	
7	5.5	1.03		17	10.5	0.02	
8	6.0	0.24		18	11.0	-0.11	
9	6.5	2.53		19	11.5	-0.91	
10	7.0	-0.13		20	12.0	1.42	

Next, we generate randomly a value of the disturbance term for each observation using a N(0,1) distribution (normal with zero mean and unit variance).

$$Y = 2.0 + 0.5X + u$$

X	2.0+0.5	X u	Y	X	2.0+0.5	X u	Y
1	2.5	-0.59	1.91	11	7.5	1.59	
2	3.0	-0.24		12	8.0	-0.92	
3	3.5	-0.83		13	8.5	-0.71	
4	4.0	0.03		14	9.0	-0.25	
5	4.5	-0.38		15	9.5	1.69	
6	5.0	-2.19		16	10.0	0.15	
7	5.5	1.03		17	10.5	0.02	
8	6.0	0.24		18	11.0	-0.11	
9	6.5	2.53		19	11.5	-0.91	
10	7.0	-0.13		20	12.0	1.42	

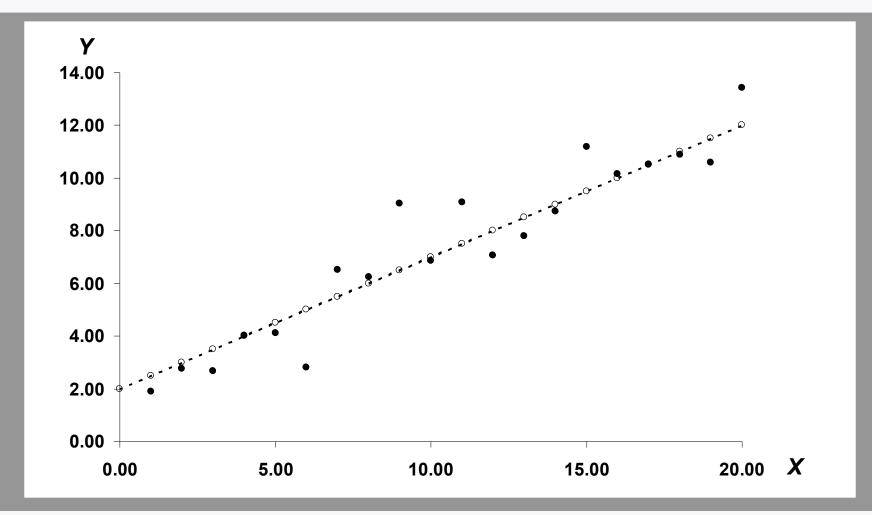
Thus, for example, the value of Y in the first observation is 1.91, not 2.50.

$$Y = 2.0 + 0.5X + u$$

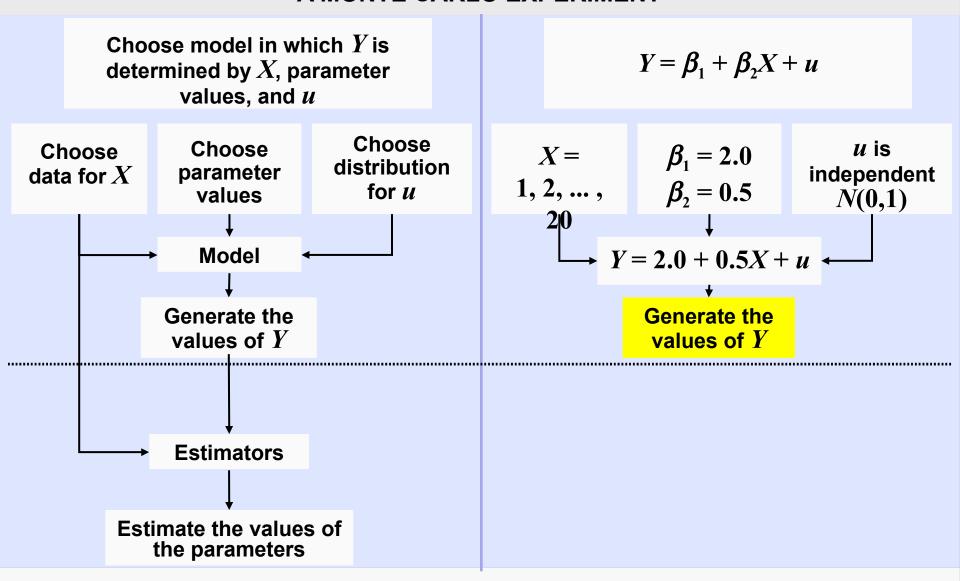
X	2.0+0.5	X u	Y	X 2.0+0.5X u Y	
1	2.5	-0.59	1.91	11 7.5 1.59 9.09	
2	3.0	-0.24	2.76	12 8.0 -0.92 7.08	
3	3.5	-0.83	2.67	13 8.5 -0.71 7.79	
4	4.0	0.03	4.03	14 9.0 -0.25 8.75	
5	4.5	-0.38	4.12	15 9.5 1.69 11.19	
6	5.0	-2 .19	2.81	16 10.0 0.15 10.15	
7	5.5	1.03	6.53	17 10.5 0.02 10.52	
8	6.0	0.24	6.24	18 11.0 -0.11 10.89	
9	6.5	2.53	9.03	19 11.5 -0.91 10.59	
10	7.0	-0.13	6.87	20 12.0 1.42 13.42	

Similarly, we generate values of Y for the other 19 observations.

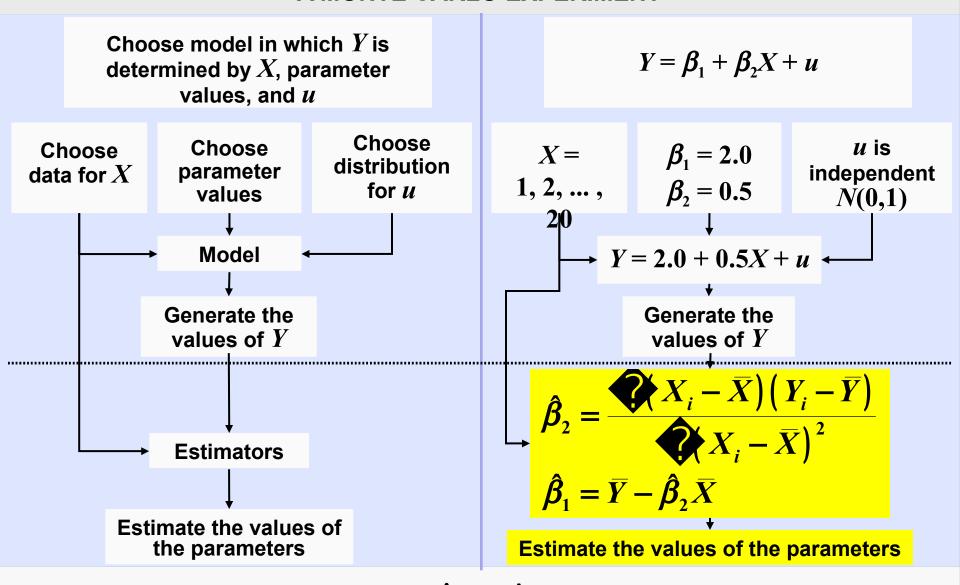
$$Y = 2.0 + 0.5X + u$$



The 20 observations are displayed graphically.

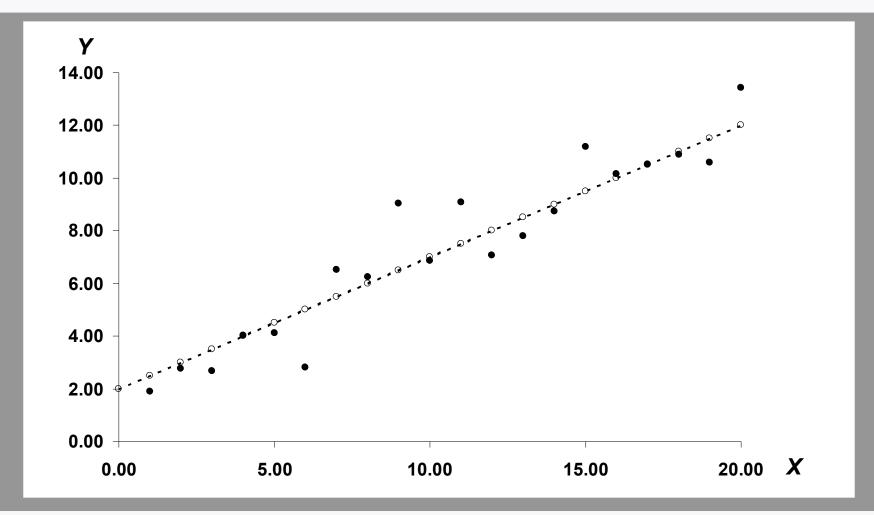


We have reached this point in the Monte Carlo experiment.



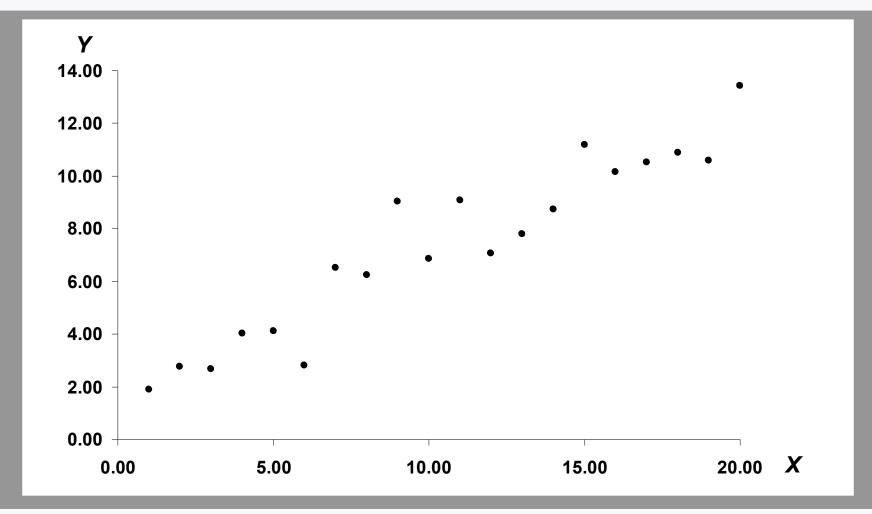
We will now apply the OLS estimators for $\hat{\beta}_1$ and $\hat{\beta}_2$ to the data for X and Y, and see how well the estimates correspond to the true values.

$$Y = 2.0 + 0.5X + u$$



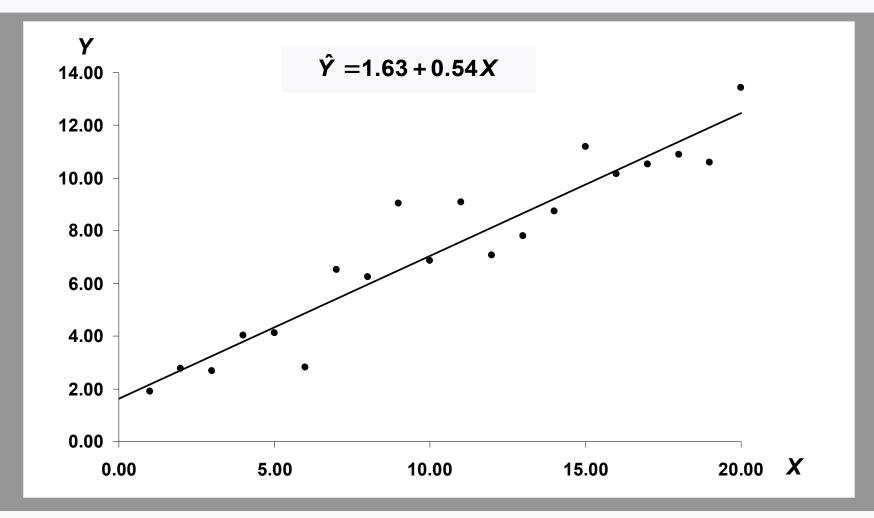
Here is the scatter diagram again.

$$Y = 2.0 + 0.5X + u$$



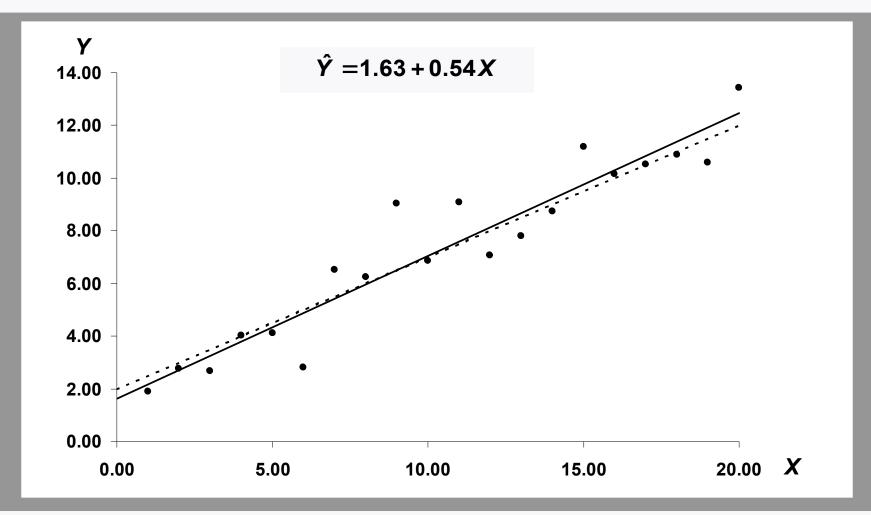
The regression estimators use only the observed data for X and Y.

$$Y = 2.0 + 0.5X + u$$



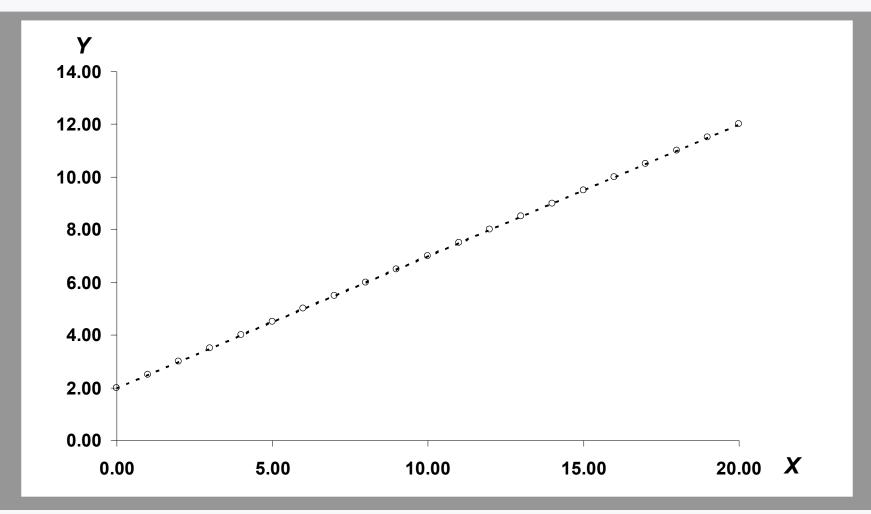
Here is the regression equation fitted to the data.

$$Y = 2.0 + 0.5X + u$$



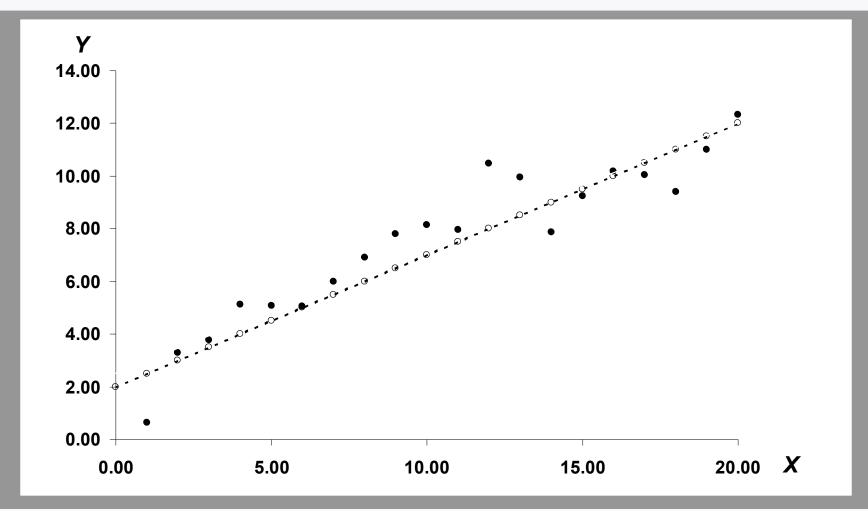
For comparison, the nonstochastic component of the true relationship is also displayed. β_2 (true value 0.50) has been overestimated and β_1 (true value 2.00) has been underestimated.

$$Y = 2.0 + 0.5X + u$$



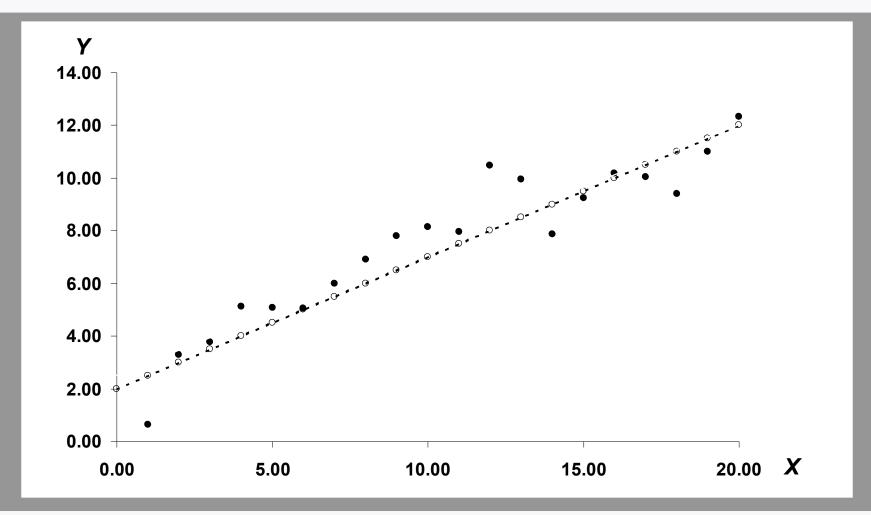
We will repeat the process, starting with the same nonstochastic components of Y.

$$Y = 2.0 + 0.5X + u$$



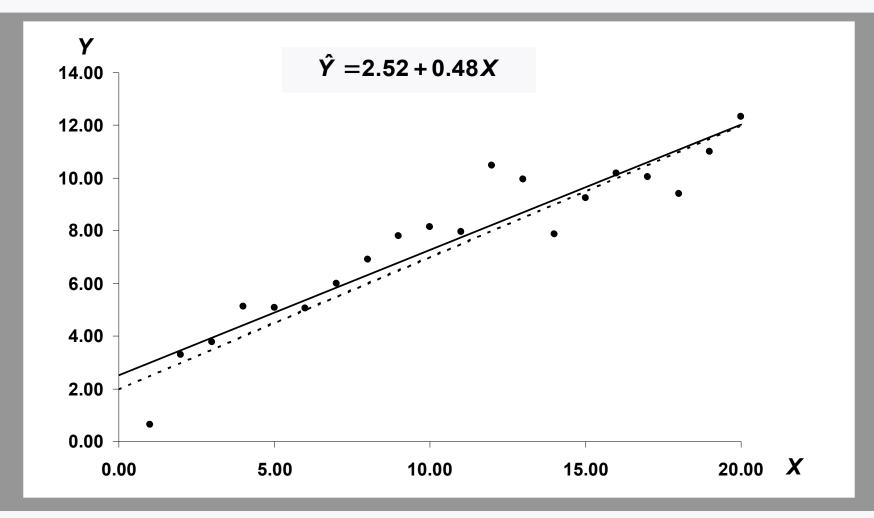
As before, the values of Y are modified by adding randomly-generated values of the disturbance term.

$$Y = 2.0 + 0.5X + u$$



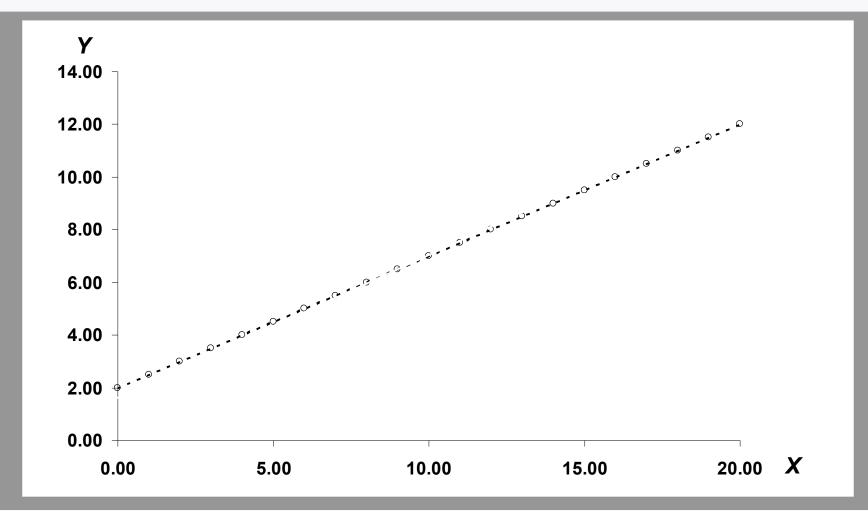
The new values of the disturbance term are drawn from the same N(0,1) distribution as the previous ones but, except by coincidence, will be different from them.

$$Y = 2.0 + 0.5X + u$$



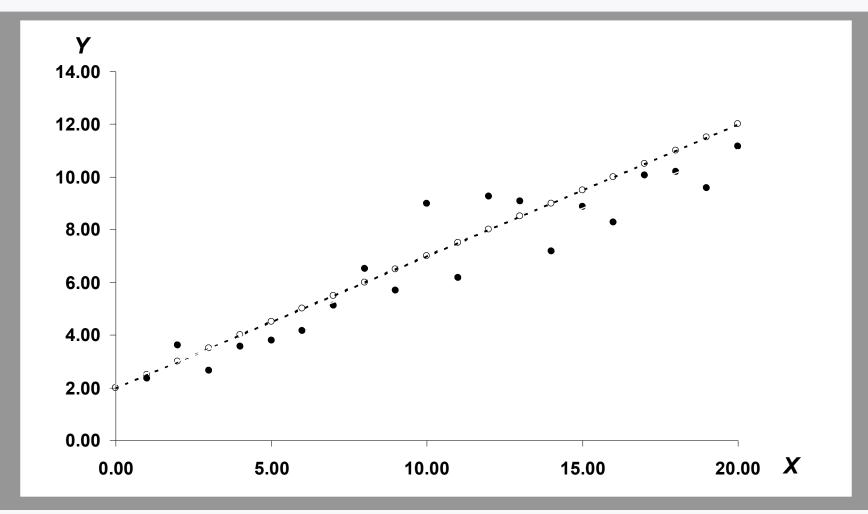
This time the slope coefficient has been underestimated and the intercept overestimated.

$$Y = 2.0 + 0.5X + u$$



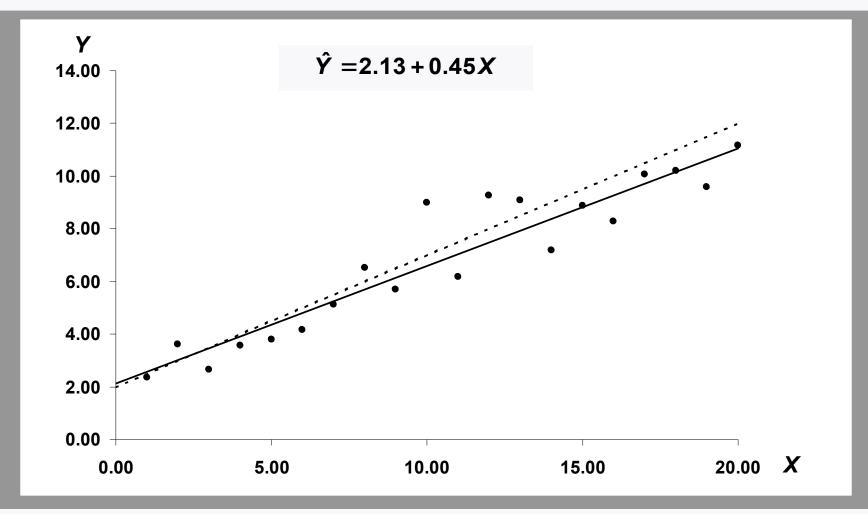
We will repeat the process once more.

$$Y = 2.0 + 0.5X + u$$



A new set of random numbers has been used in generating the values of Y.

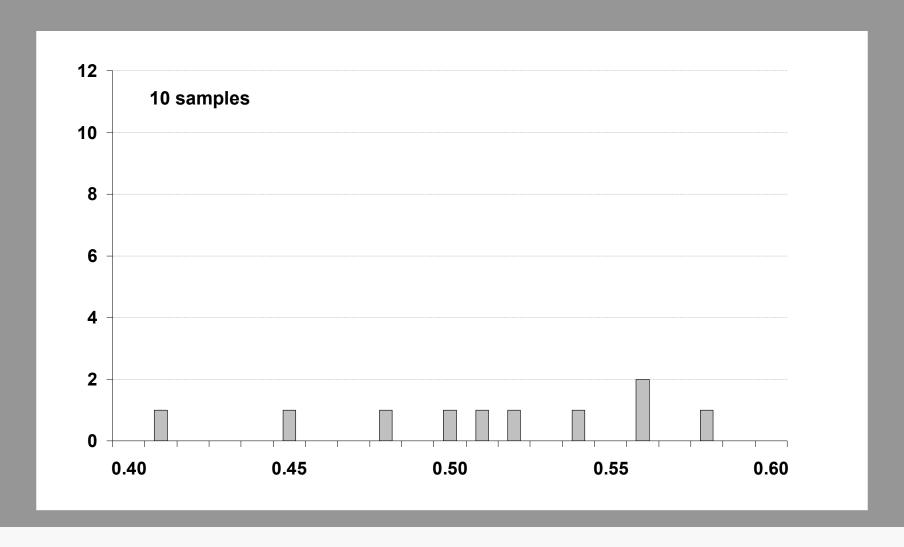
$$Y = 2.0 + 0.5X + u$$



As last time, the slope coefficient has been underestimated and the intercept overestimated.

sample	$\hat{\pmb{\beta}}_{_{1}}$	$\boldsymbol{\hat{\beta}}_{\scriptscriptstyle 2}$	
1	1.63	0.54	
2	2.52	0.48	
3	2.13	0.45	
4	2.14	0.50	
5	1.71	0.56	
6	1.81	0.51	
7	1.72	0.56	
8	3.18	0.41	
9	1.26	0.58	
10	1.94	0.52	

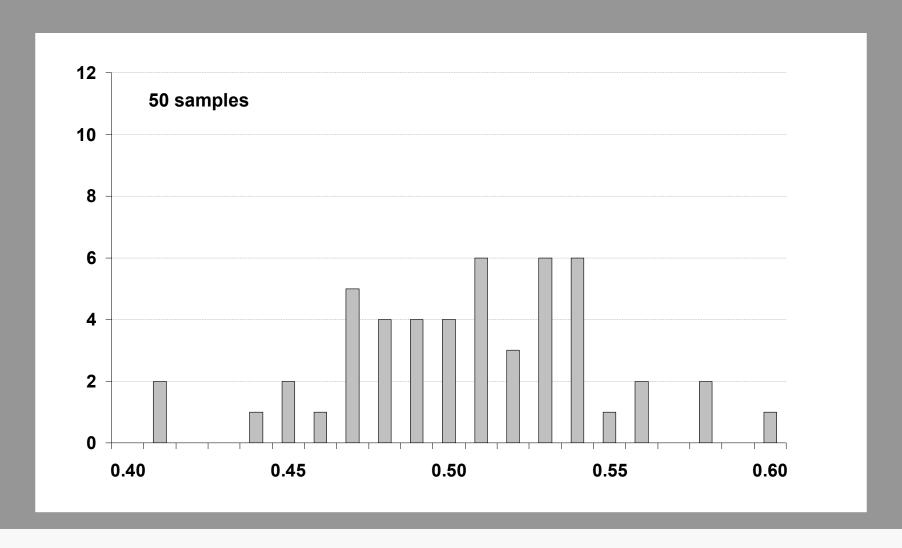
The table summarizes the results of the three regressions and adds those obtained repeating the process a further seven times.



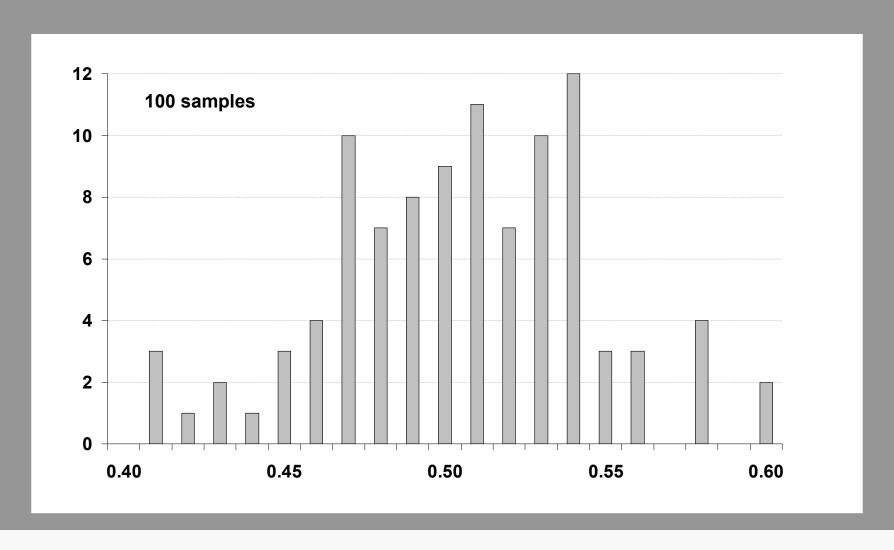
Here is a histogram for the estimates of β_2 . Nothing much can be seen yet.

1–10	11–20	21-30	31-40	41–50
0.54	0.49	0.54	0.52	0.49
0.48	0.54	0.46	0.47	0.50
0.45	0.49	0.45	0.54	0.48
0.50	0.54	0.50	0.53	0.44
0.56	0.54	0.41	0.51	0.53
0.51	0.52	0.53	0.51	0.48
0.56	0.49	0.53	0.47	0.47
0.41	0.53	0.47	0.55	0.50
0.58	0.60	0.51	0.51	0.53
0.52	0.48	0.47	0.58	0.51

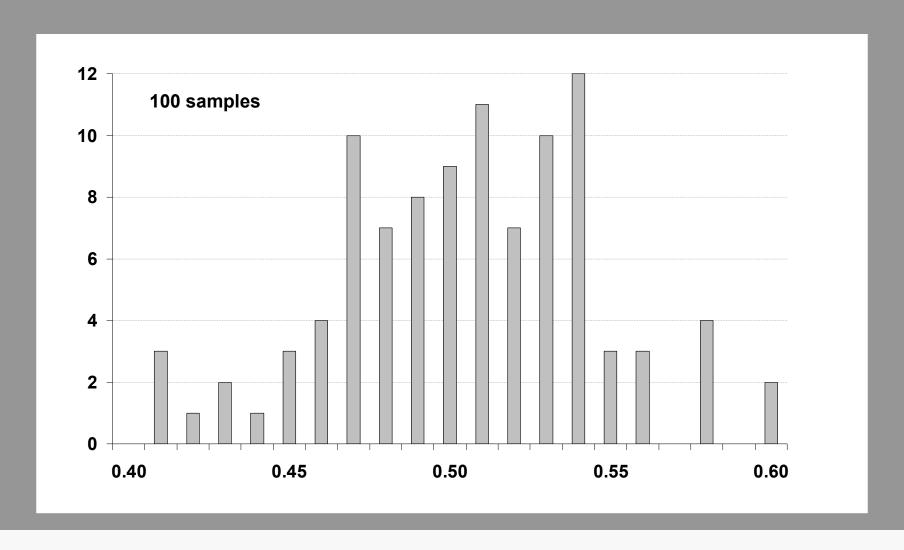
Here are the estimates of β_2 obtained with 40 further replications of the process.



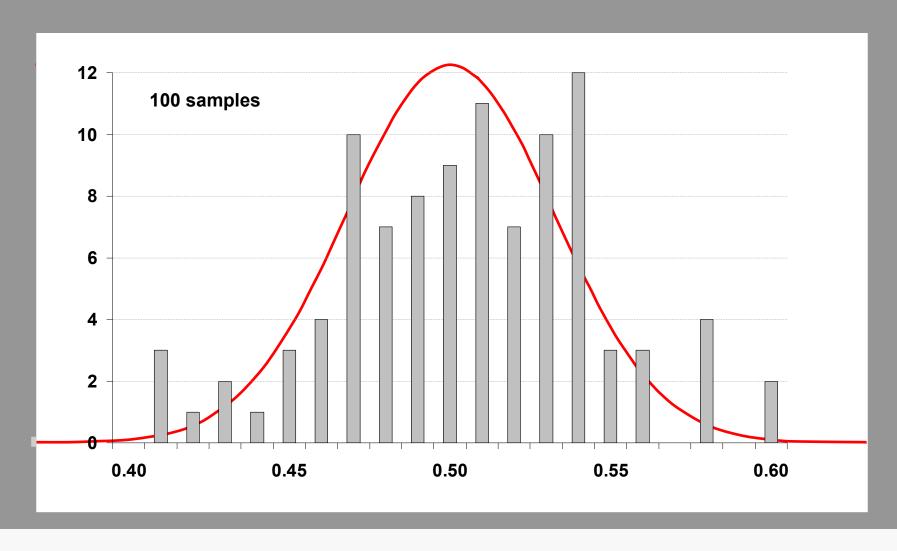
The histogram is beginning to display a central tendency.



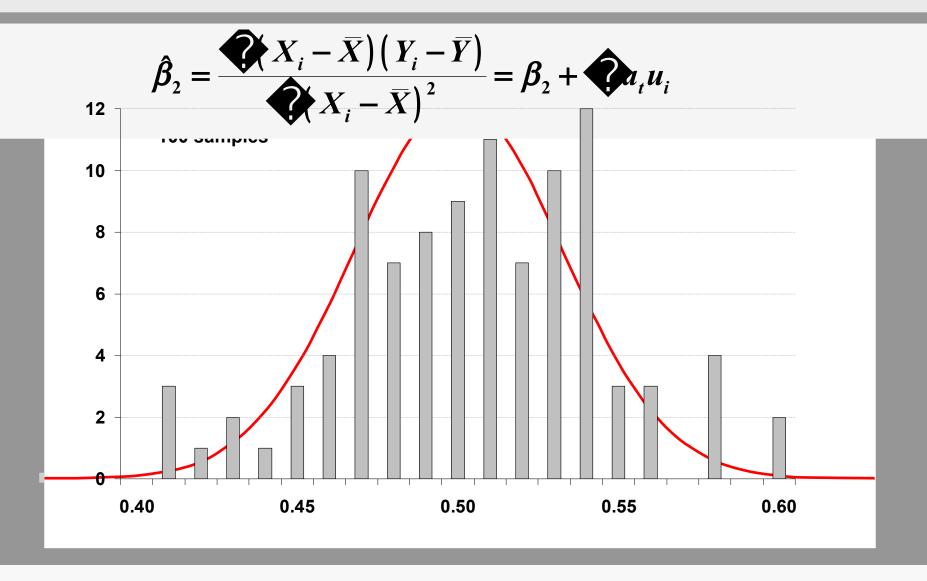
This is the histogram with 100 replications. We can see that the distribution appears to be symmetrical around the true value, implying that the estimator is unbiased.



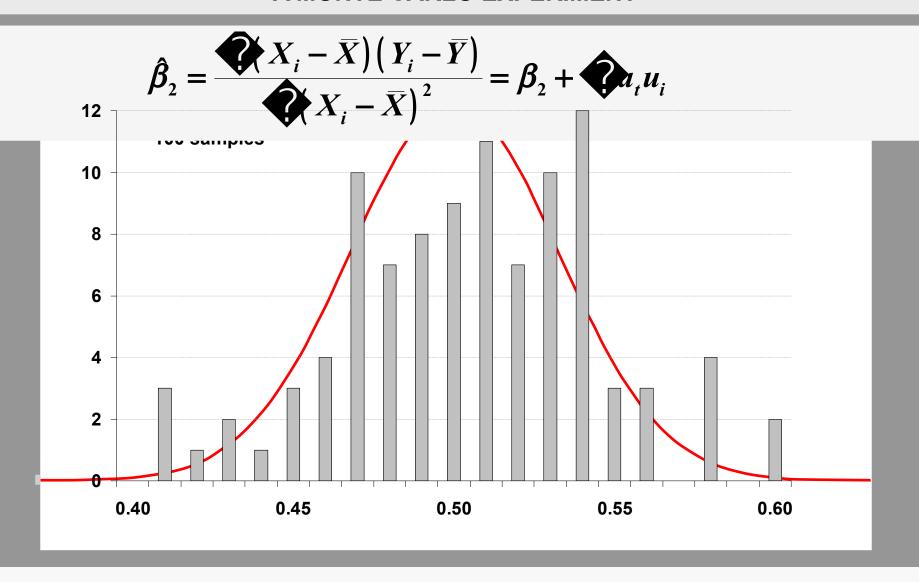
However, the distribution is still rather jagged. It would be better to repeat the process 1,000,000 times, perhaps more.



The red curve shows the limiting shape of the distribution. It is symmetrical around the true value, indicating that the estimator is unbiased.



The distribution is normal because the random component of the coefficient is a weighted linear combination of the values of the disturbance term in the observations in the sample. We demonstrated this in the previous slideshow.



We are assuming (Assumption A.6) that the disturbance term in each observation has a normal distribution. A linear combination of normally distributed random variables itself has a normal distribution.

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