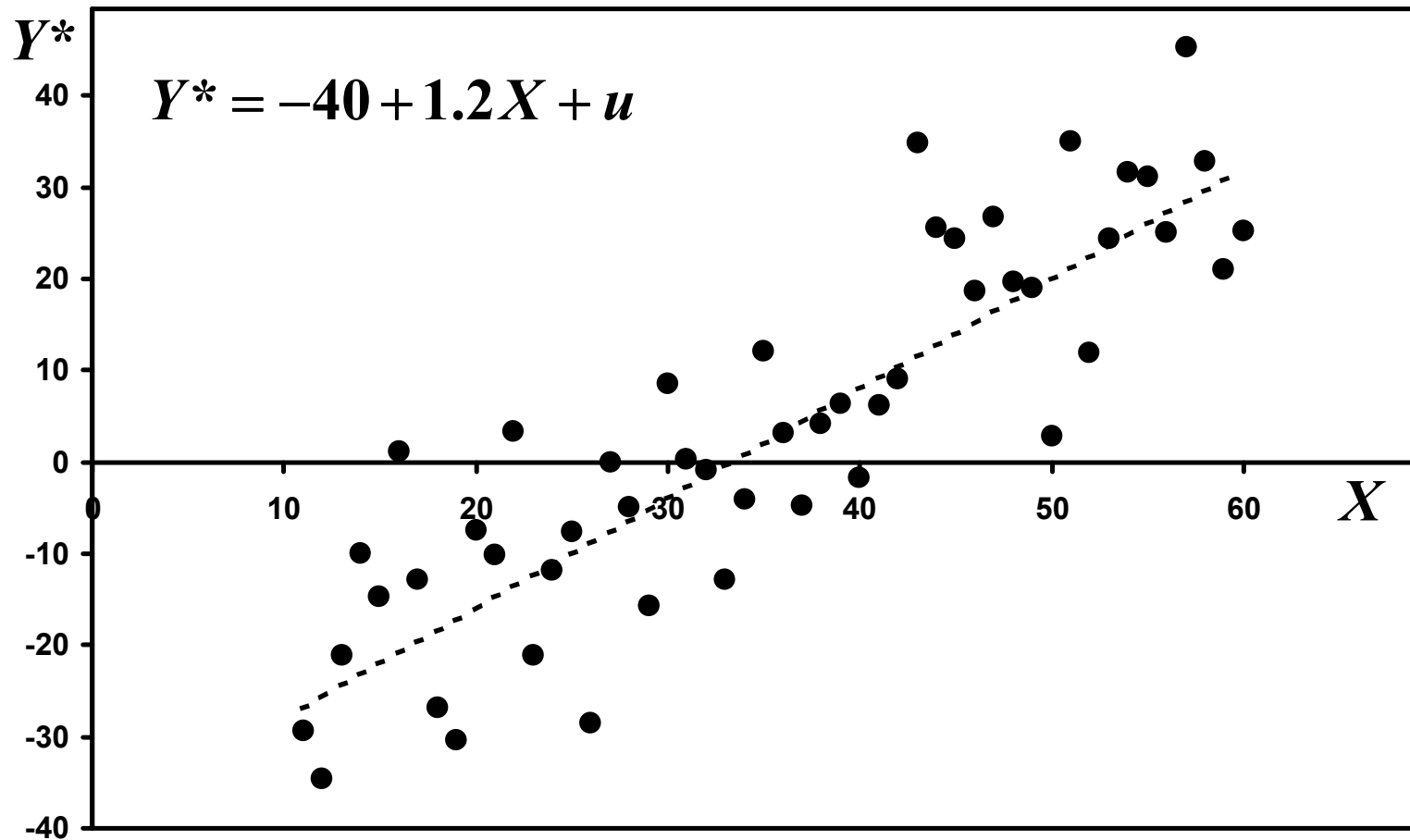


## TOBIT ANALYSIS

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

**Sometimes the dependent variable in a regression model is subject to a lower limit or an upper limit, or both. Suppose that in the absence of any constraints,  $Y$  is related to  $X$  by the model shown.**

# TOBIT ANALYSIS



For example, suppose that the true relationship is as shown, and that, given a set of random numbers for the disturbance term drawn from a normal distribution with mean 0 and standard deviation 10, we have a sample of observations as shown.

## TOBIT ANALYSIS

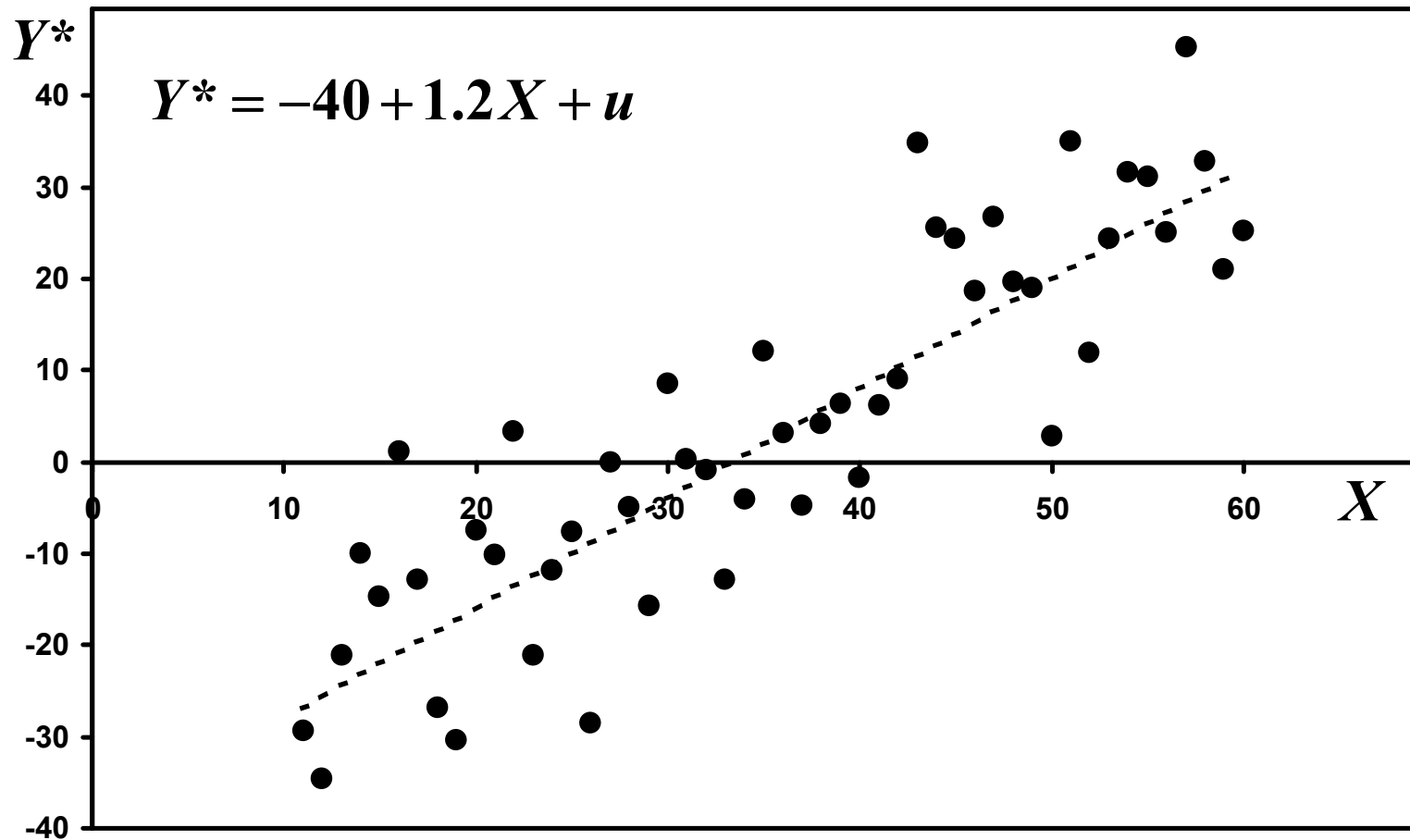
$$Y^* = \beta_1 + \beta_2 X + u$$

$$Y = Y^* \text{ if } Y^* > 0$$

$$Y = 0 \text{ if } Y^* \leq 0$$

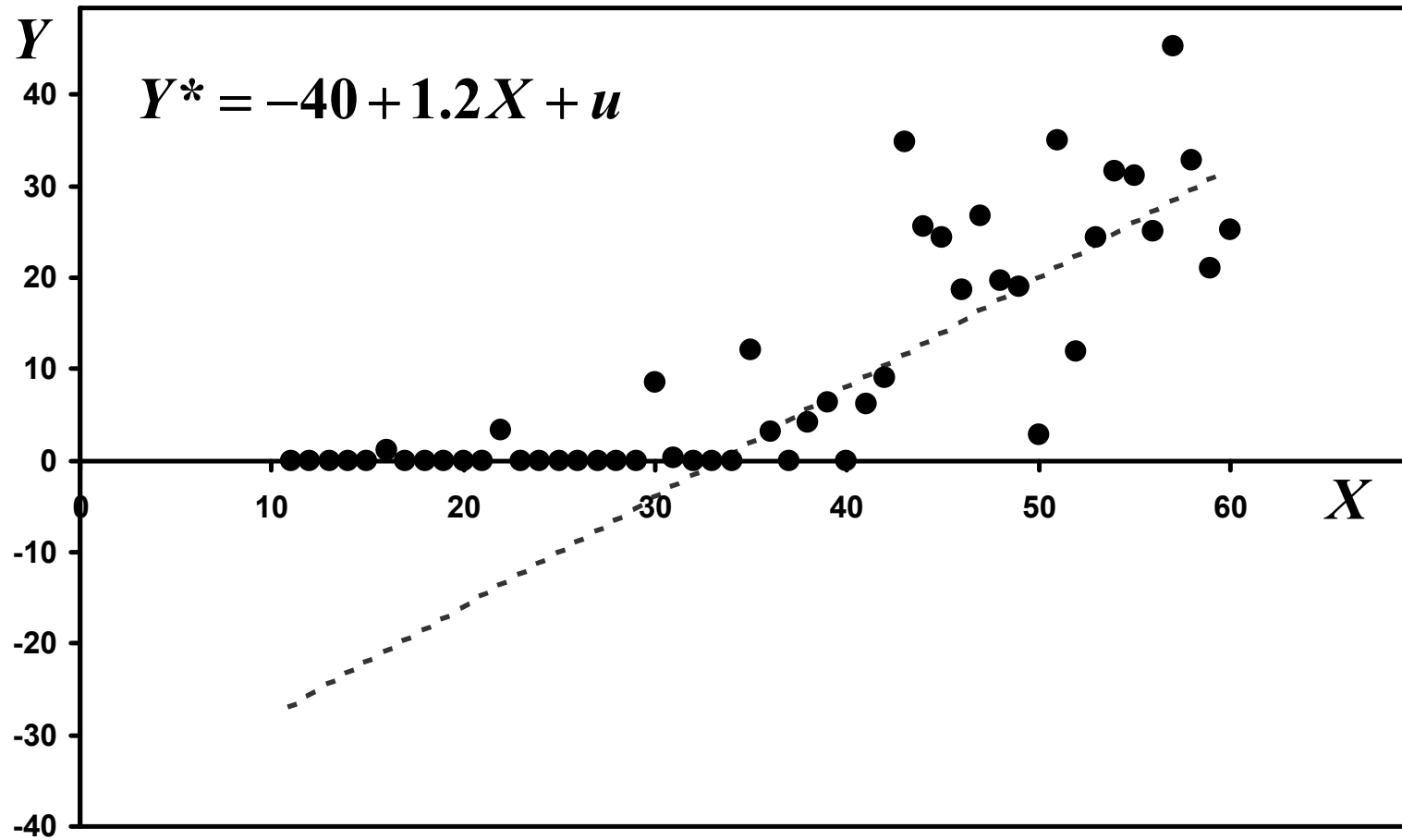
However, suppose that the dependent variable is subject to a lower bound, in this case 0. Then  $Y$  will be as given by the model if  $Y^* > 0$ , and it will be 0 if  $Y^* = 0$  or if  $Y^* < 0$ .

# TOBIT ANALYSIS



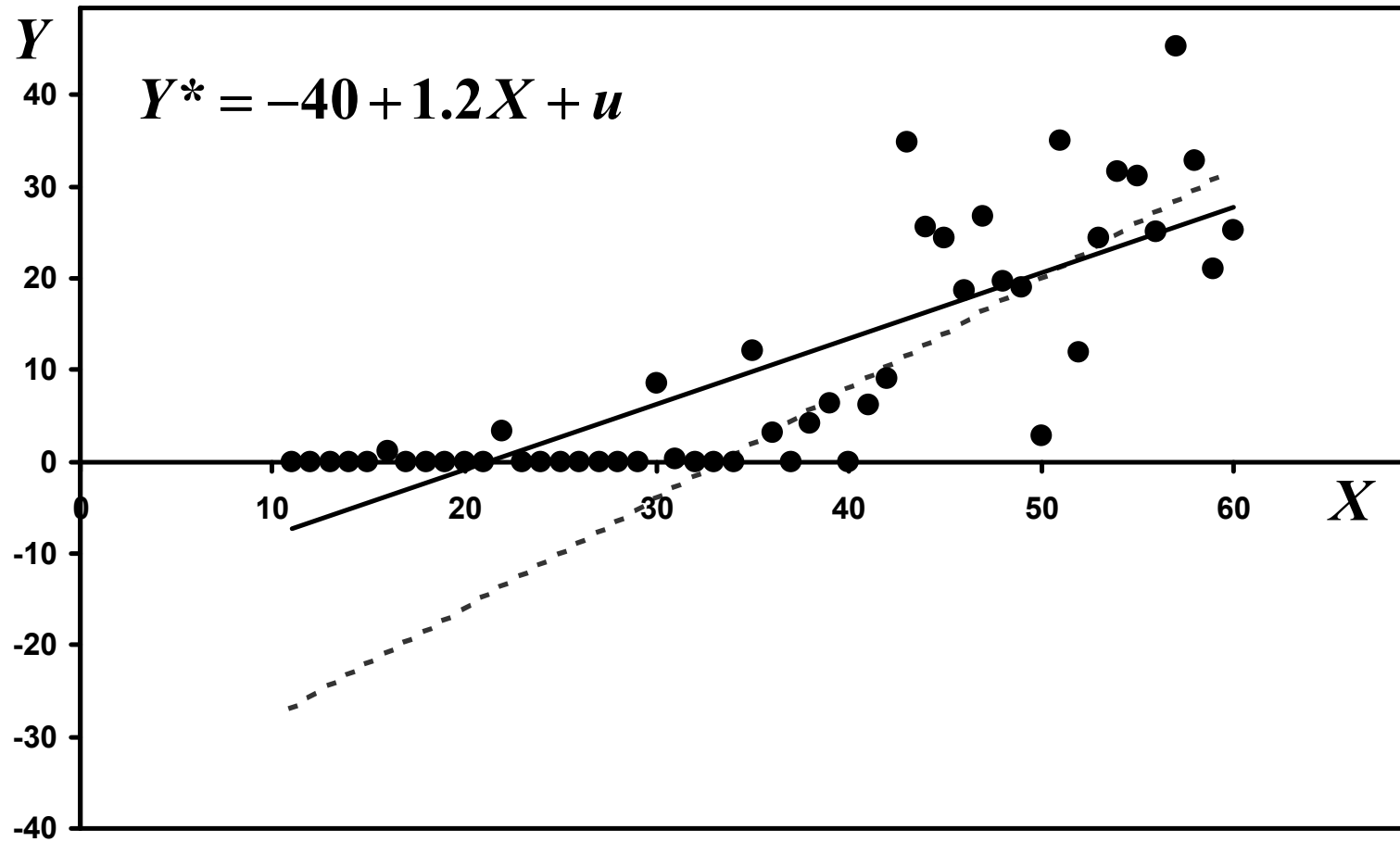
For example, suppose that we have a labor supply model with  $Y$  hours of labor supplied per week as a function of  $X$ , the wage that is offered. It is not possible to supply a negative number of hours.

# TOBIT ANALYSIS



Those individuals with negative  $Y^*$  will simply not work. For them, the actual  $Y$  is 0.

# TOBIT ANALYSIS



What would happen if we ran an OLS regression anyway? Obviously, in this case the slope coefficient would be biased downwards.

## TOBIT ANALYSIS

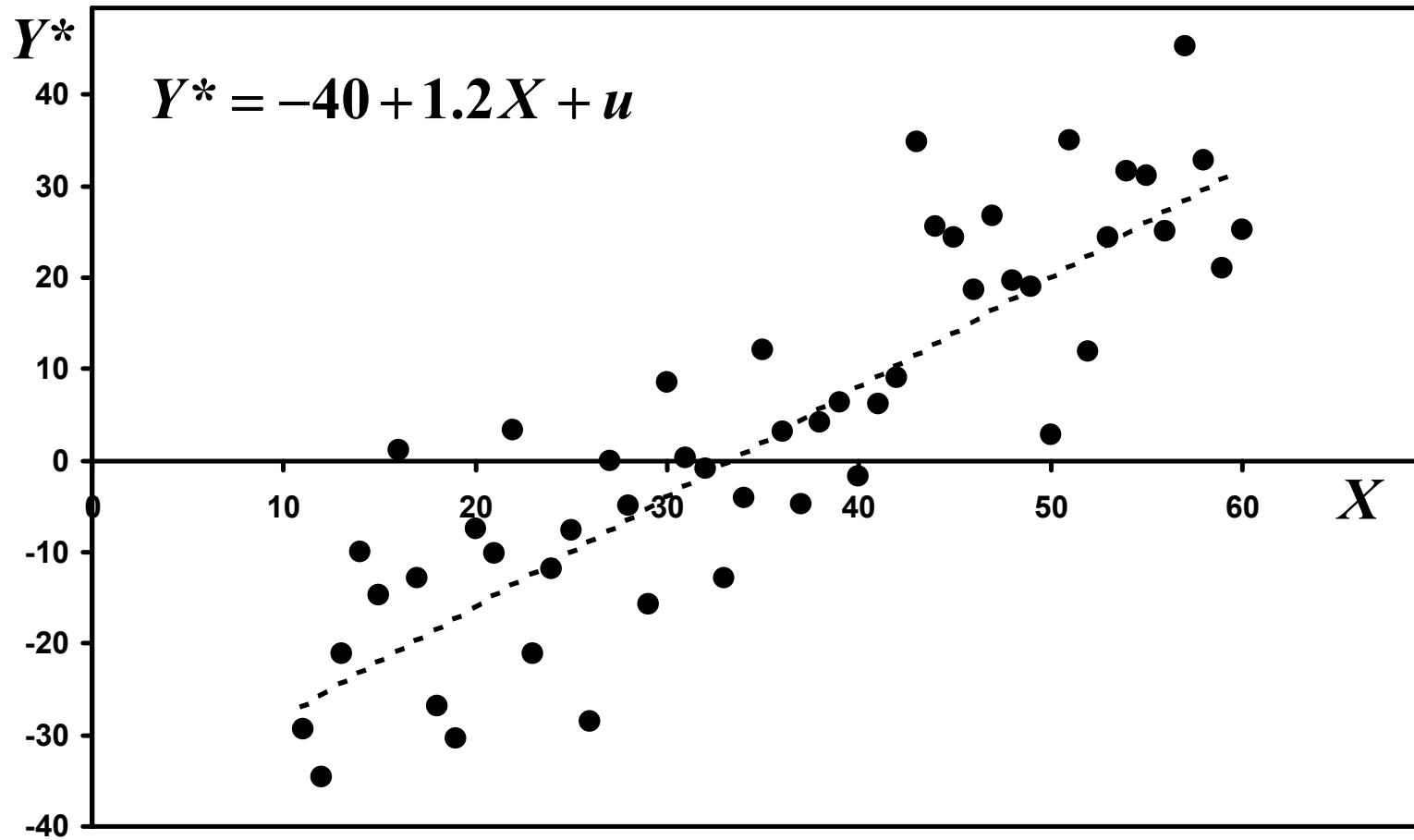
$$Y^* = \beta_1 + \beta_2 X + u$$

$$Y = Y^* \text{ if } Y^* > 0$$

**observation dropped if  $Y^* \leq 0$**

**It would be natural to suppose that the problem could be avoided by dropping the constrained observations. Unfortunately, this does not work.**

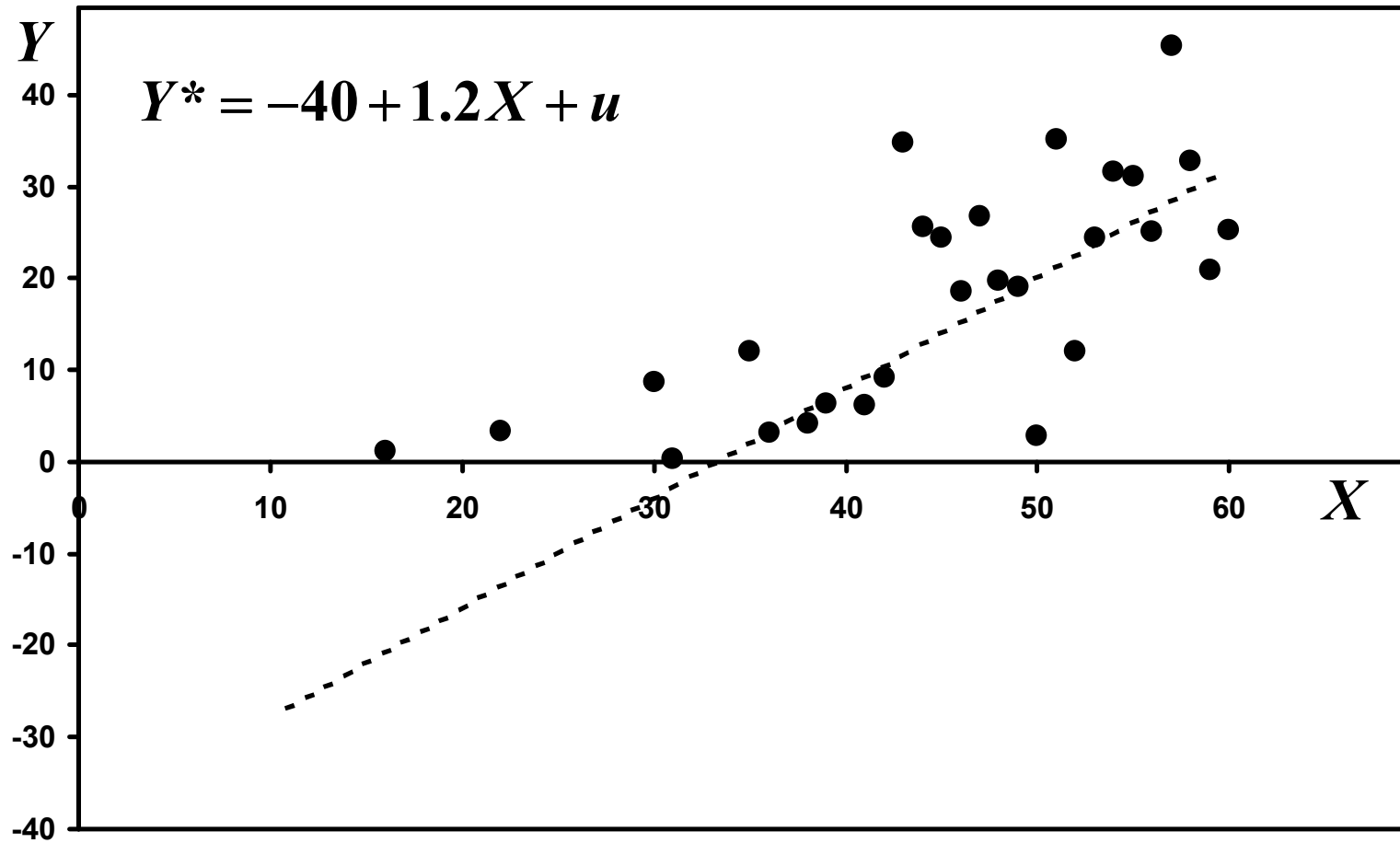
# TOBIT ANALYSIS



Here again is the sample as it would be if  $Y$  were not constrained.

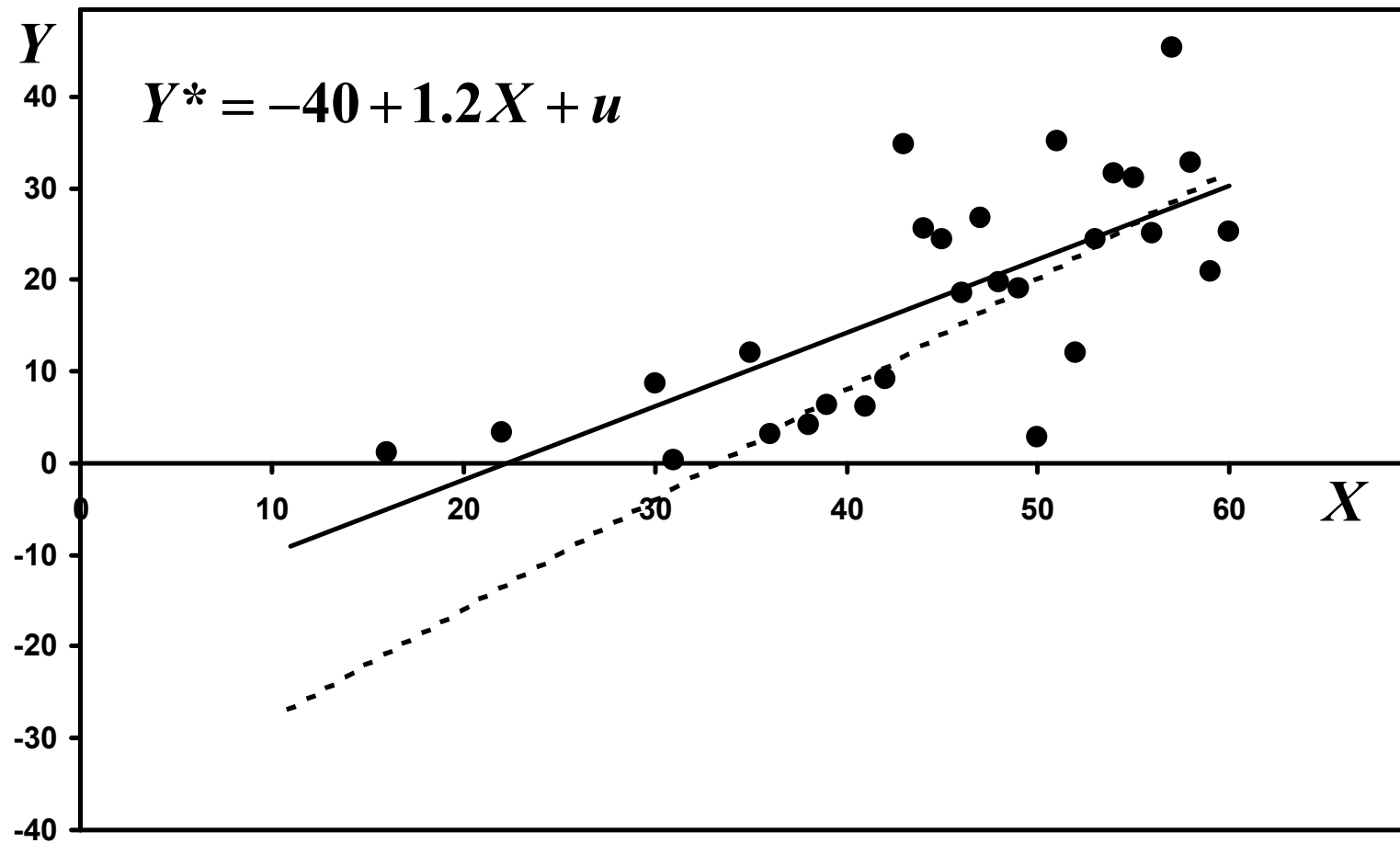


# TOBIT ANALYSIS



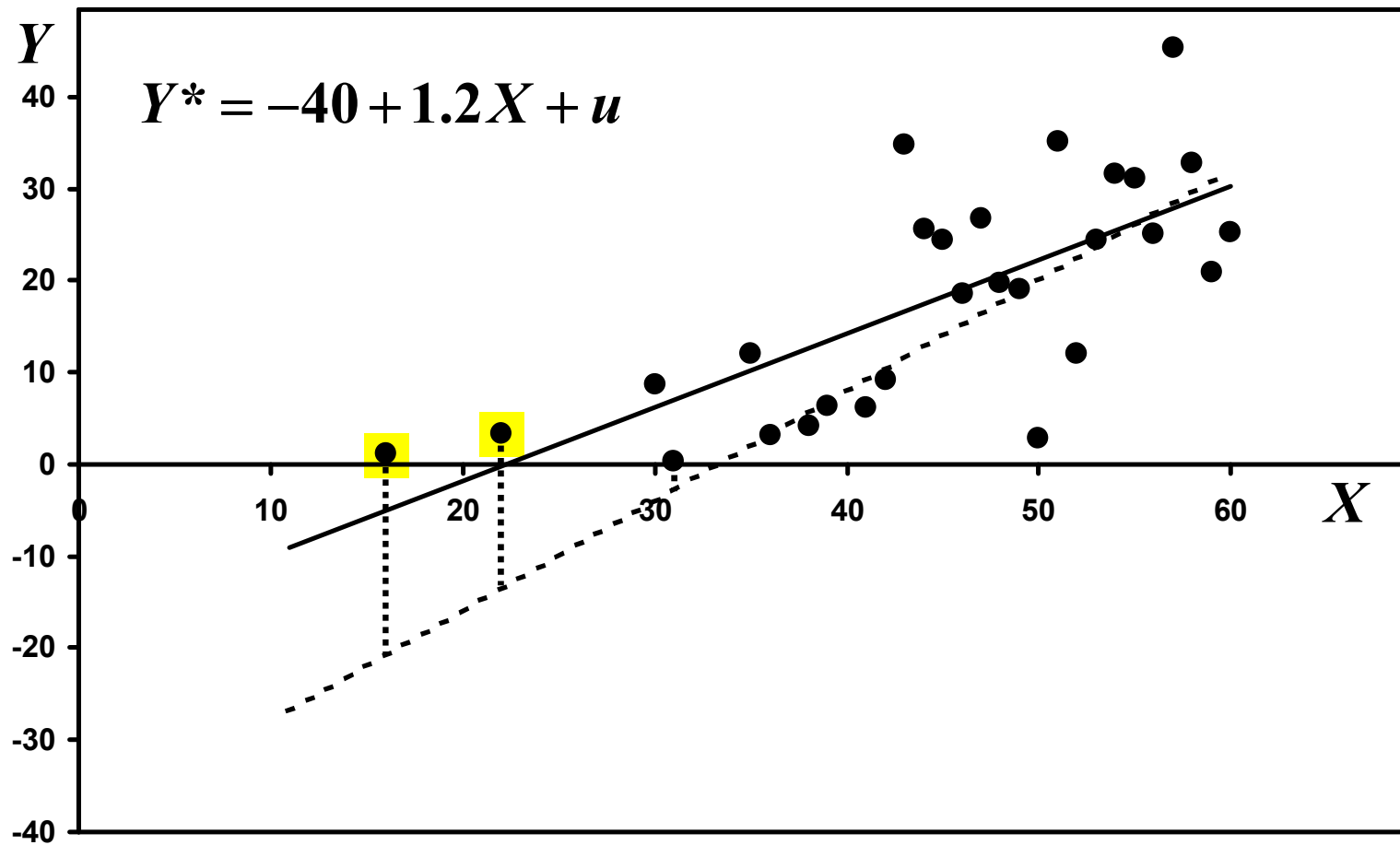
Here is the sample with the constrained observations dropped.

## TOBIT ANALYSIS



An OLS regression again yields a downwards-biased estimate of the slope coefficient and an upwards-biased estimate of the intercept. We will investigate the reason for this.

# TOBIT ANALYSIS



Look at the two observations highlighted. For such low values of  $X$ , most of the observations are constrained. The reason that these two observations appear in the sample is that their disturbance terms happen to be positive and large.

## TOBIT ANALYSIS

$$Y^* = -40 + 1.2X + u$$

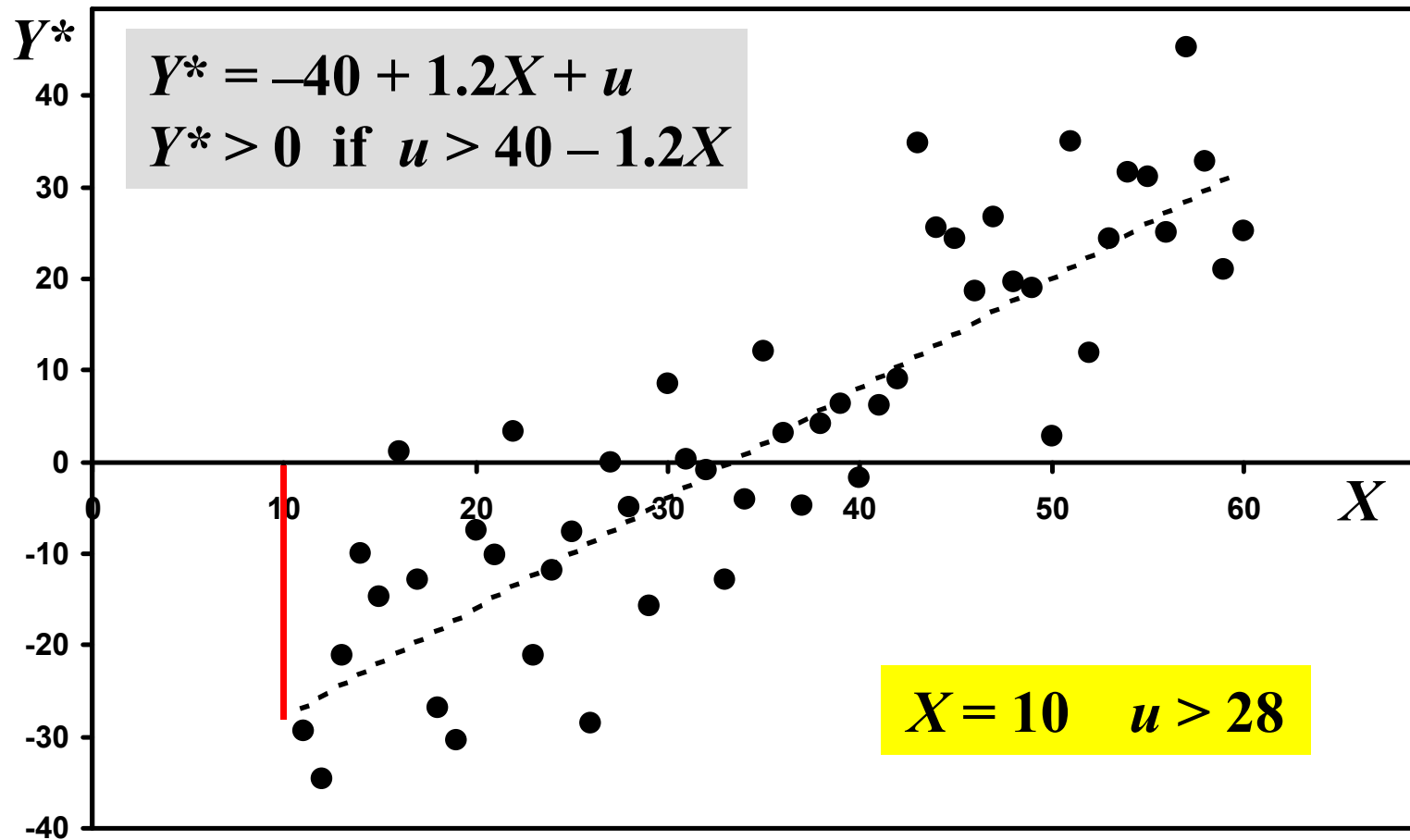
$$Y = Y^* \quad \text{if } Y^* > 0$$

observation dropped if  $Y^* \leq 0$

$$Y^* > 0 \quad \text{if } u > 40 - 1.2X$$

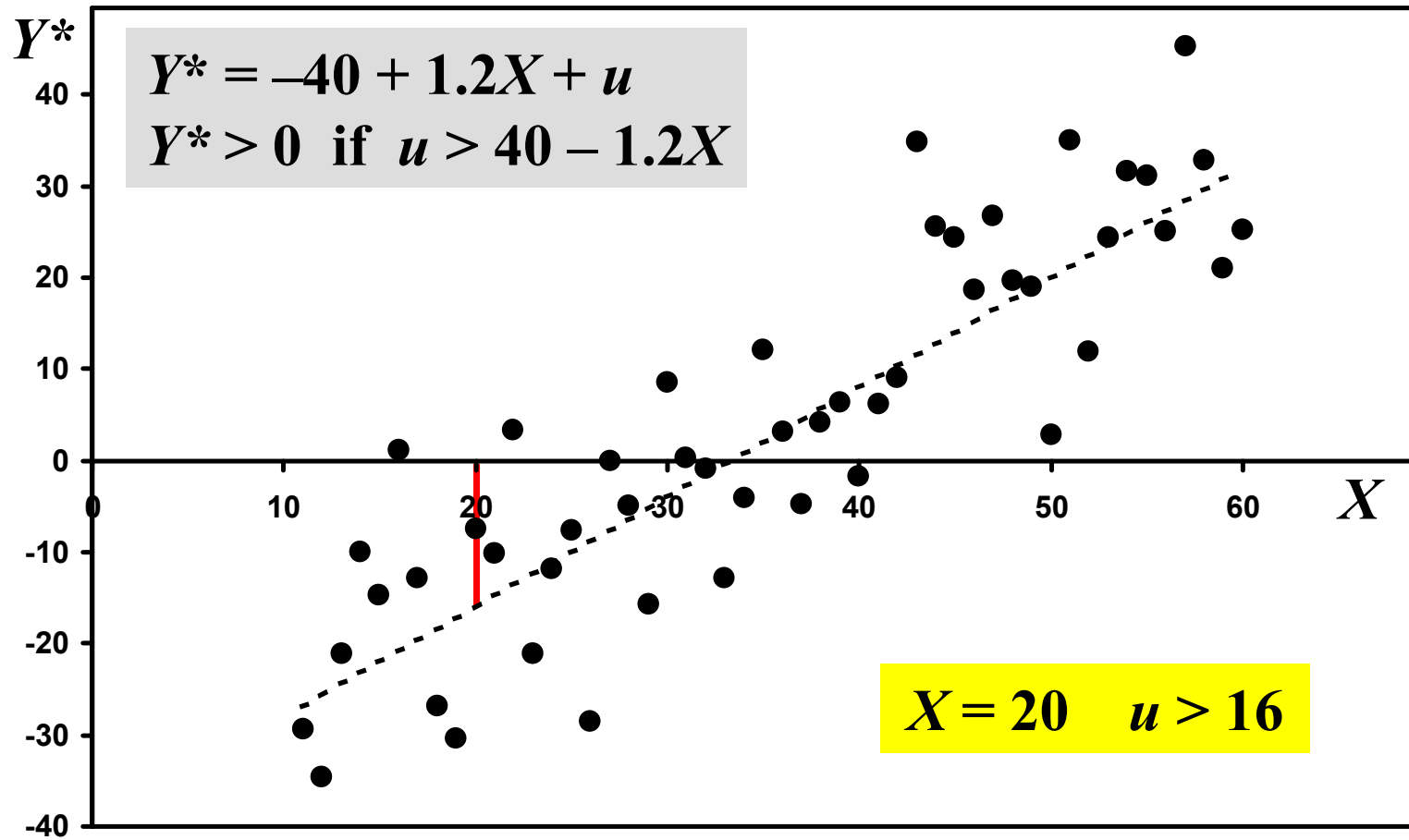
In general, for an observation to appear in the sample,  $Y^*$  must be positive, and this requires that  $u > 40 - 1.2X$ .

# TOBIT ANALYSIS



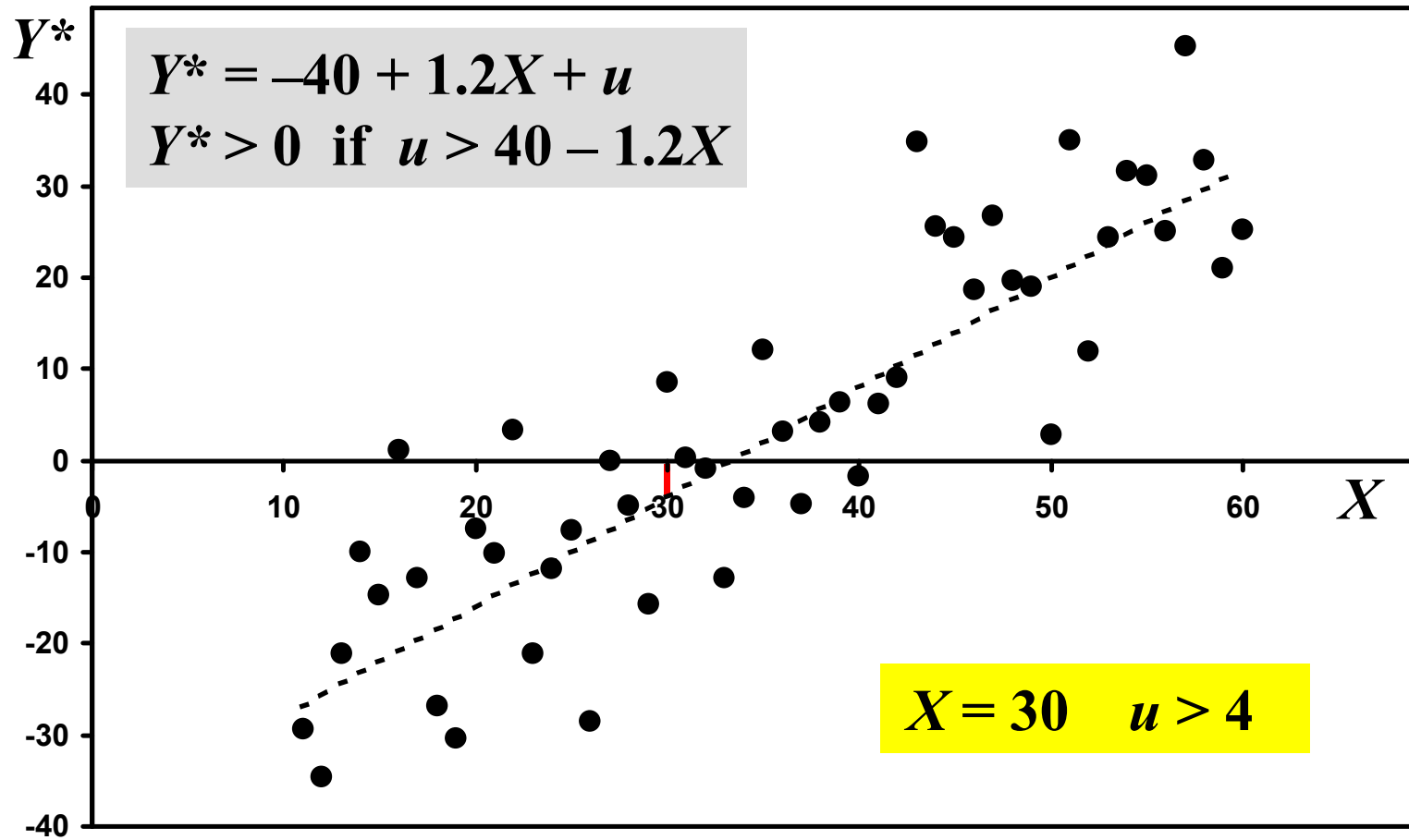
If  $X$  is equal to 10,  $u$  must be greater than 28 if the observation is to appear in the sample.

# TOBIT ANALYSIS



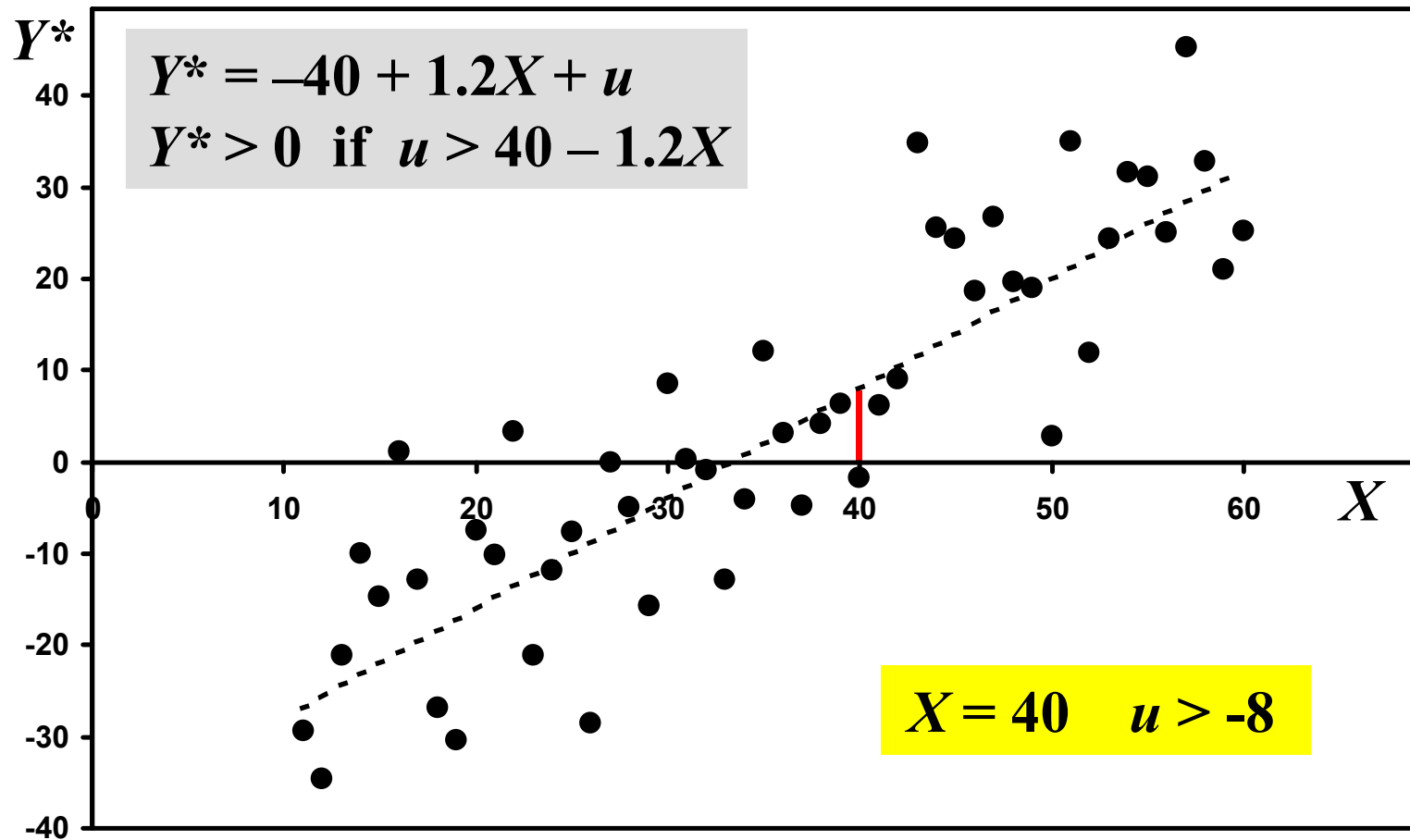
If  $X$  is equal to 20,  $u$  must be greater than 16.

# TOBIT ANALYSIS



If  $X$  is equal to 30,  $u$  must be greater than 4.

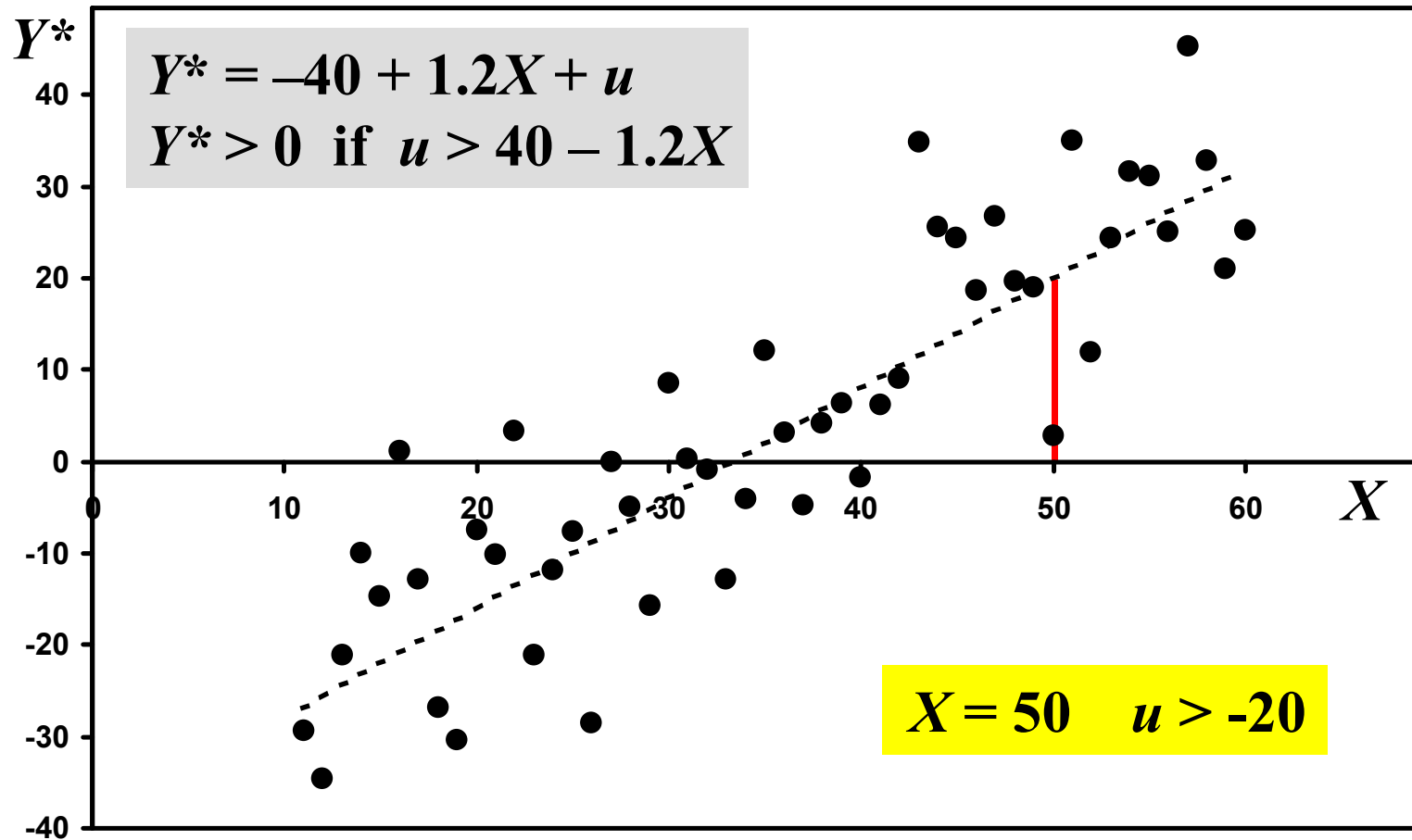
# TOBIT ANALYSIS



If  $X$  is equal to 40, the observation will appear in the sample for any positive value of  $u$  and even some negative ones. The condition is that  $u$  must be greater than  $-8$ .

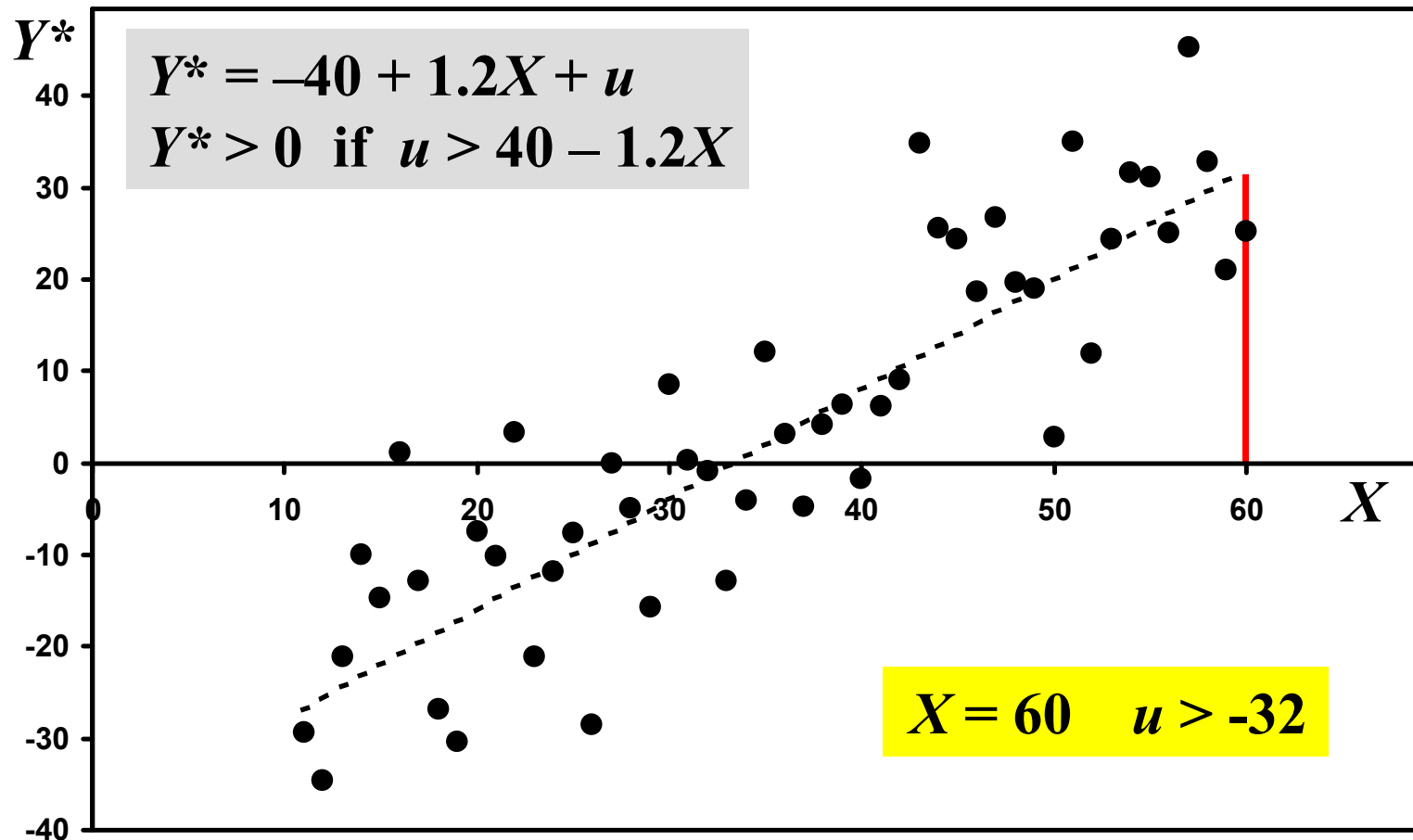


# TOBIT ANALYSIS



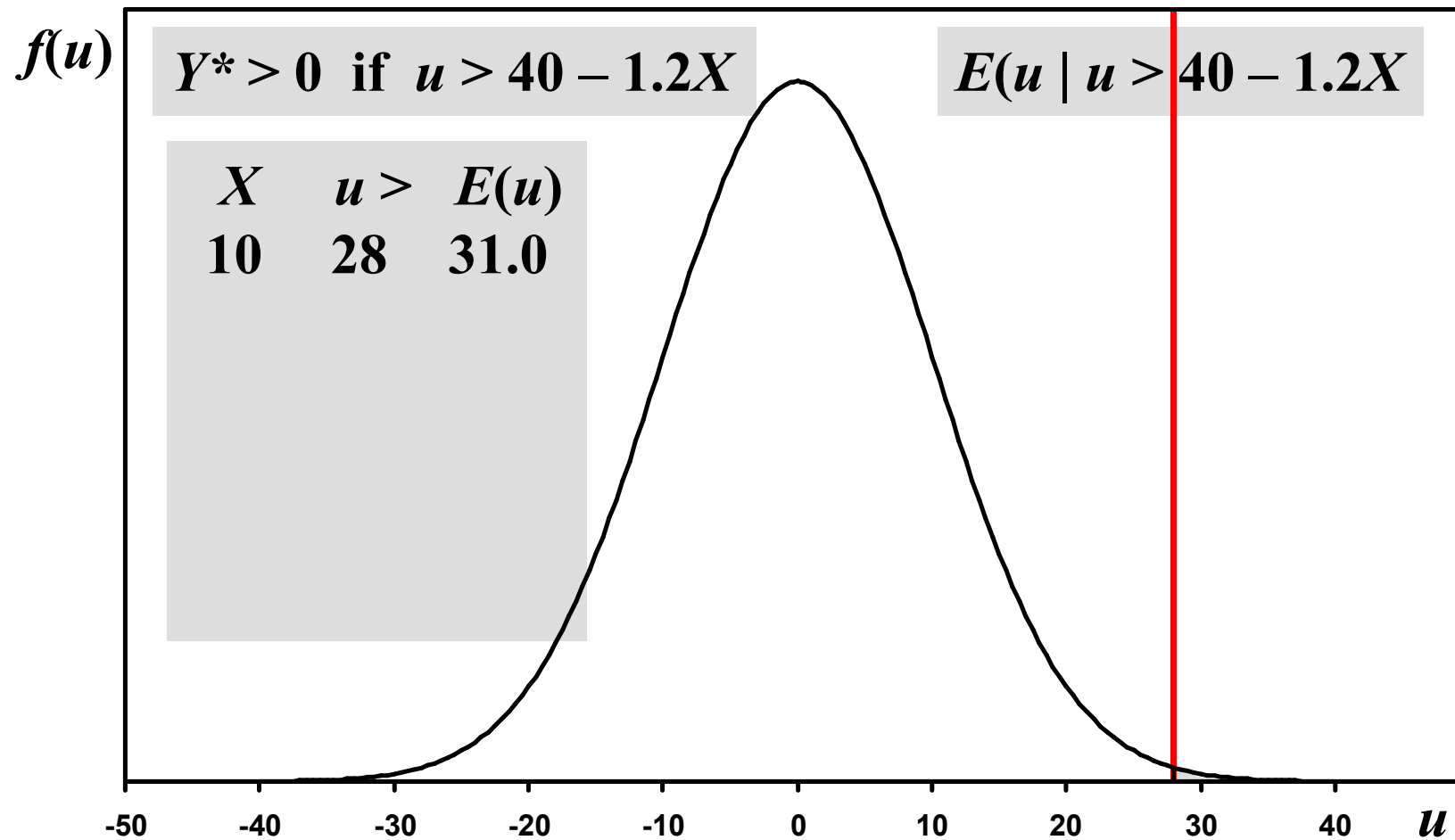
If  $X$  is equal to 50,  $u$  must be greater than  $-20$ .

# TOBIT ANALYSIS



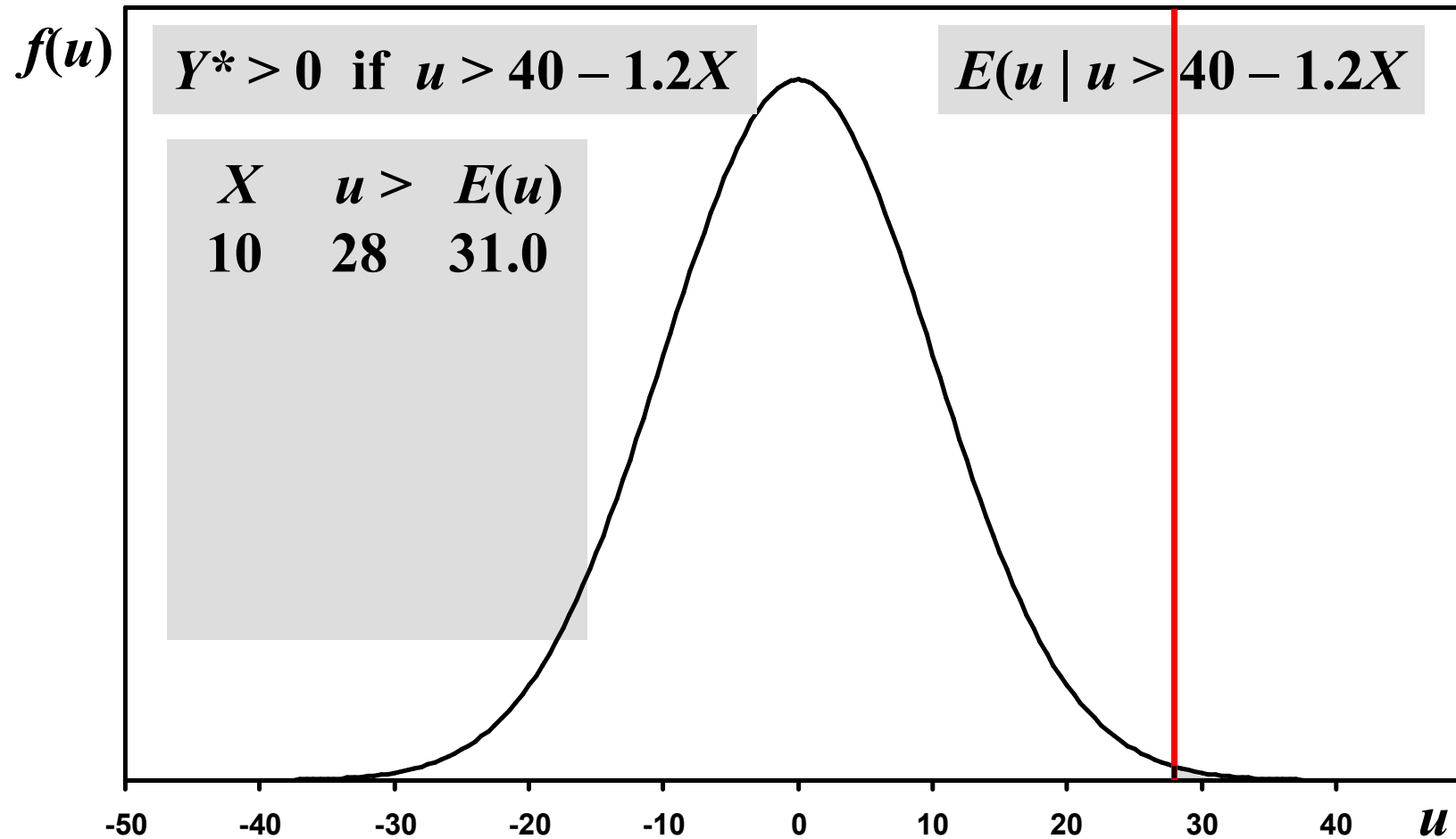
If  $X$  is equal to 60,  $u$  must be greater than  $-32$ . A value of less than  $-32$  is very unlikely, so in this part of the sample virtually every observation will appear.

# TOBIT ANALYSIS



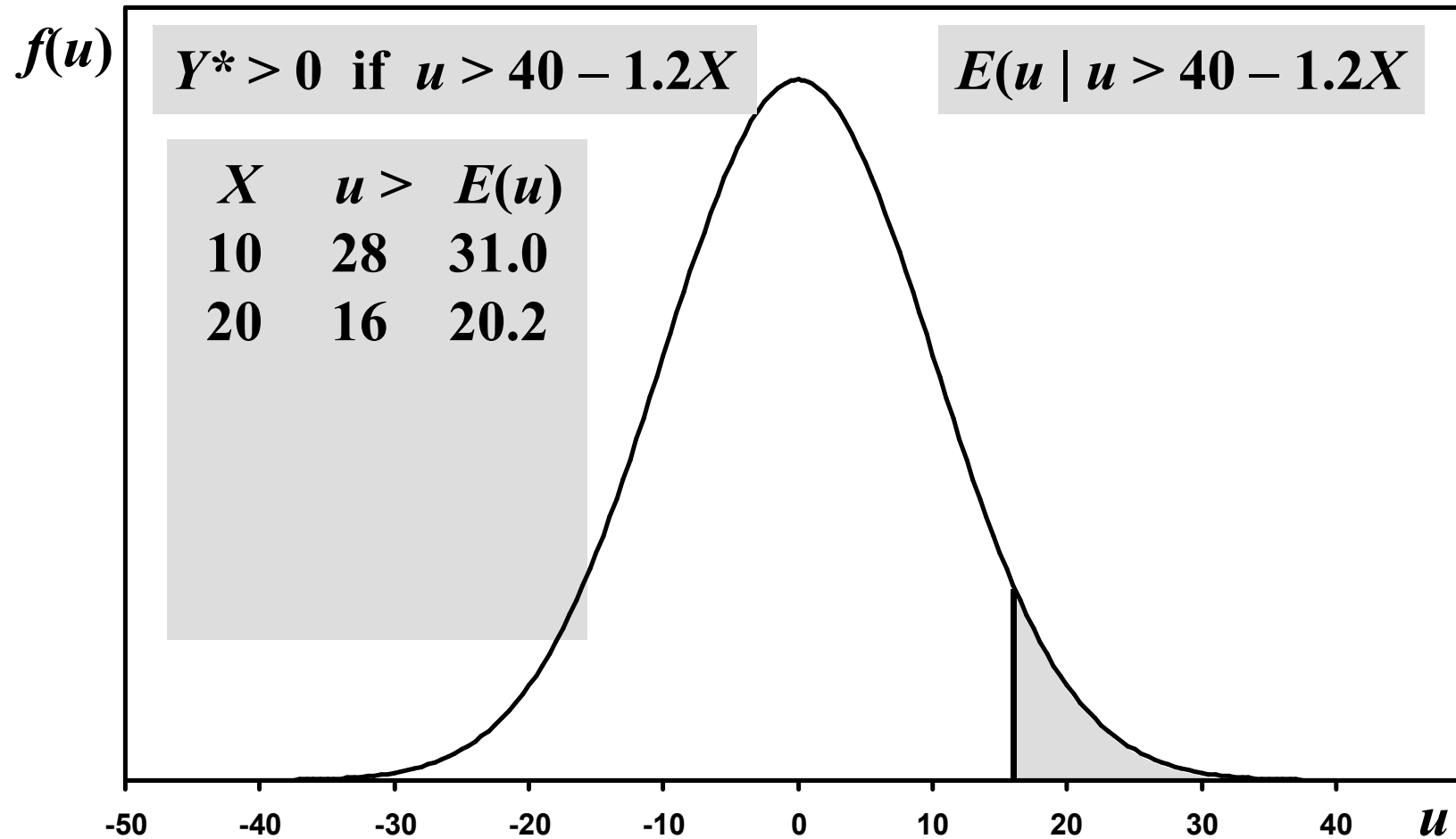
We will now show that, for observations that appear in the sample, there is a negative correlation between  $X$  and  $u$ .

# TOBIT ANALYSIS



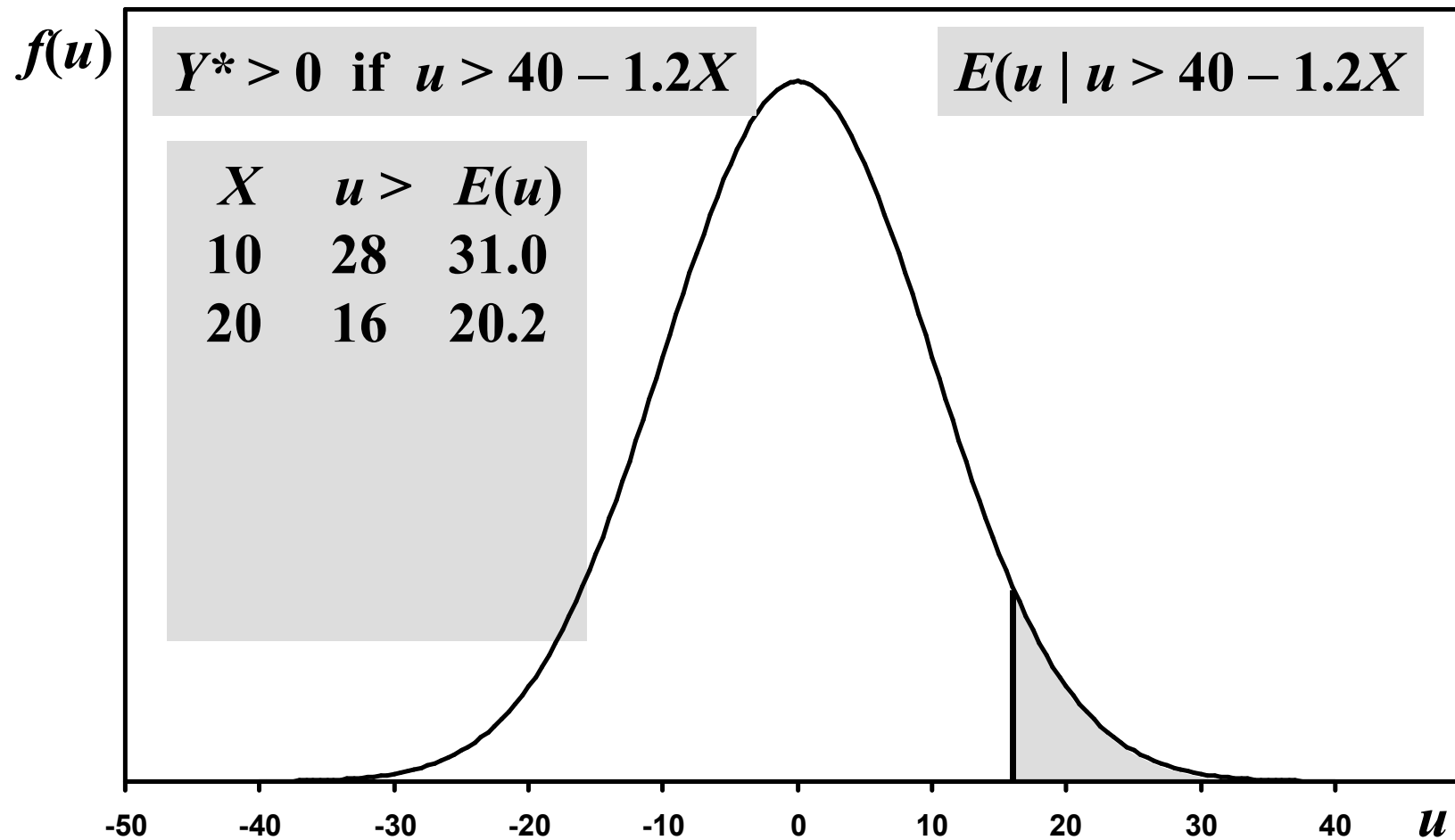
When  $X$  is equal to 10,  $u$  must be greater than 28. The expected value of  $u$  for observations appearing in the sample is its expected value in the tail to the right of the red line. It turns out to be 31.0.

# TOBIT ANALYSIS



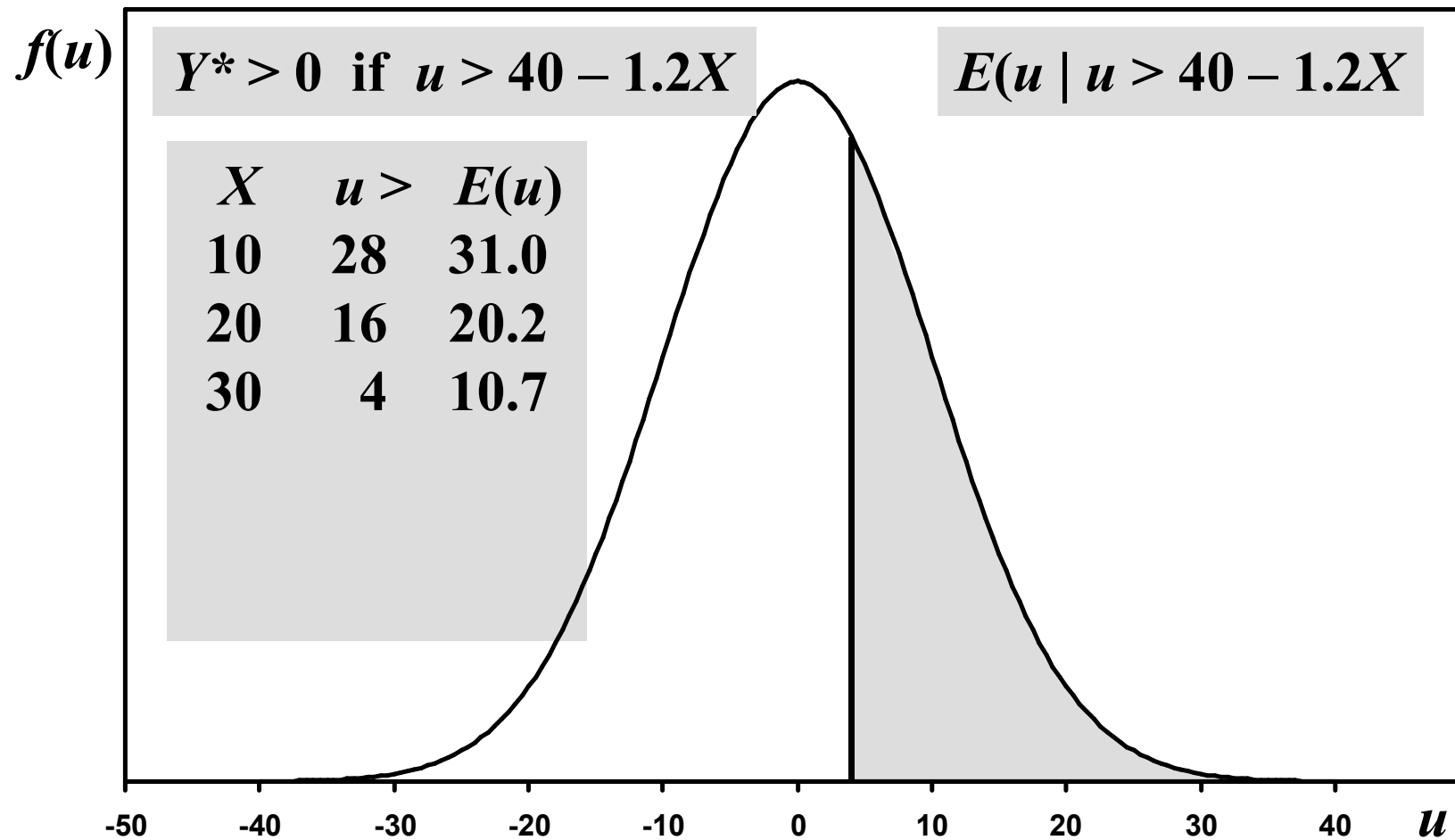
When  $X$  is equal to 20,  $u$  must be greater than 16. The expected value of  $u$ , for observations that appear in the sample, is the expected value in the shaded area. This is 20.2.

# TOBIT ANALYSIS



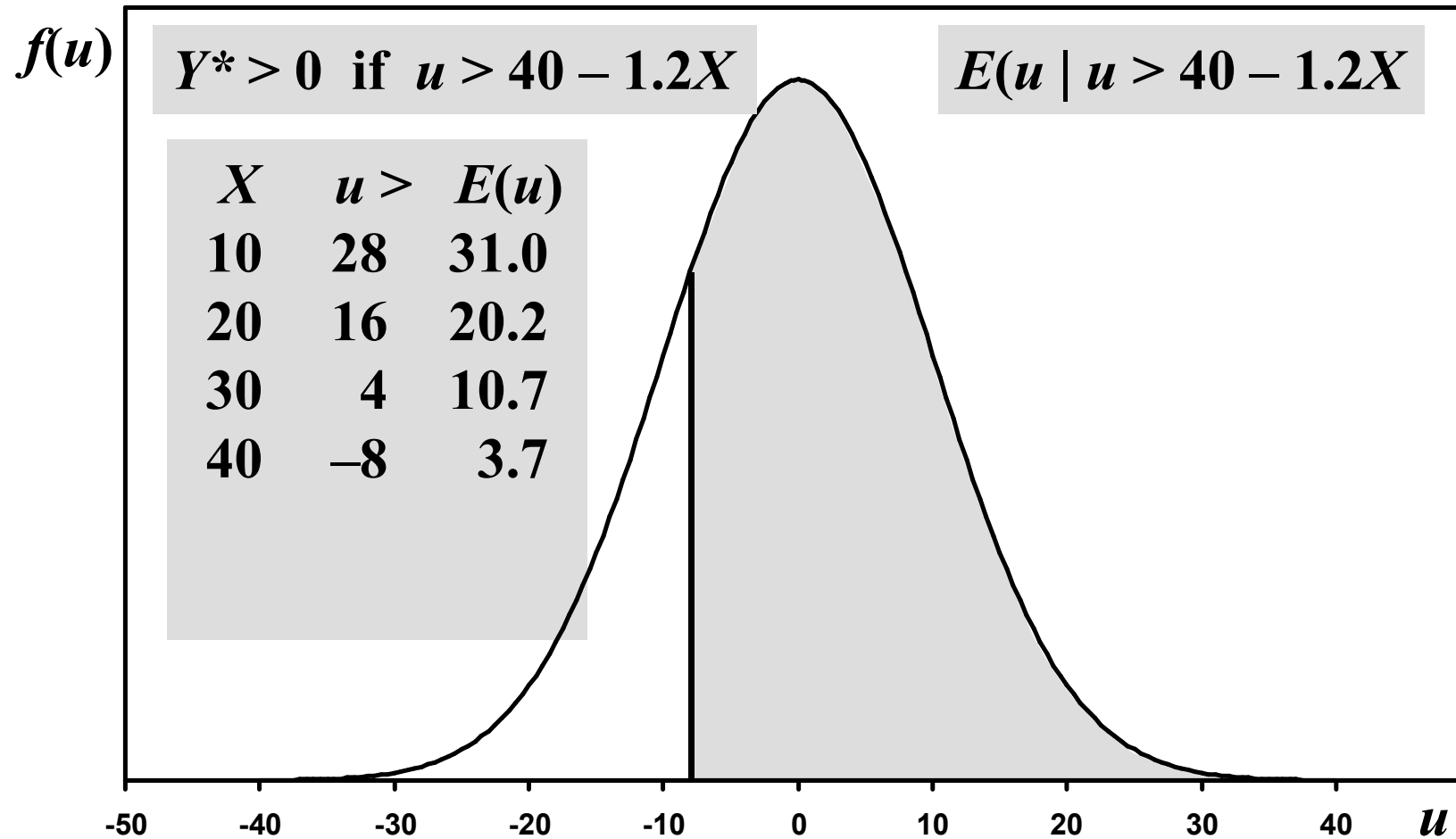
The rest of the distribution is irrelevant because an observation cannot appear in the sample if  $u < 16$ .

# TOBIT ANALYSIS



When  $X$  is equal to 30,  $u$  must be greater than 4. Its expected value, conditional on it being greater than 4, is 10.7.

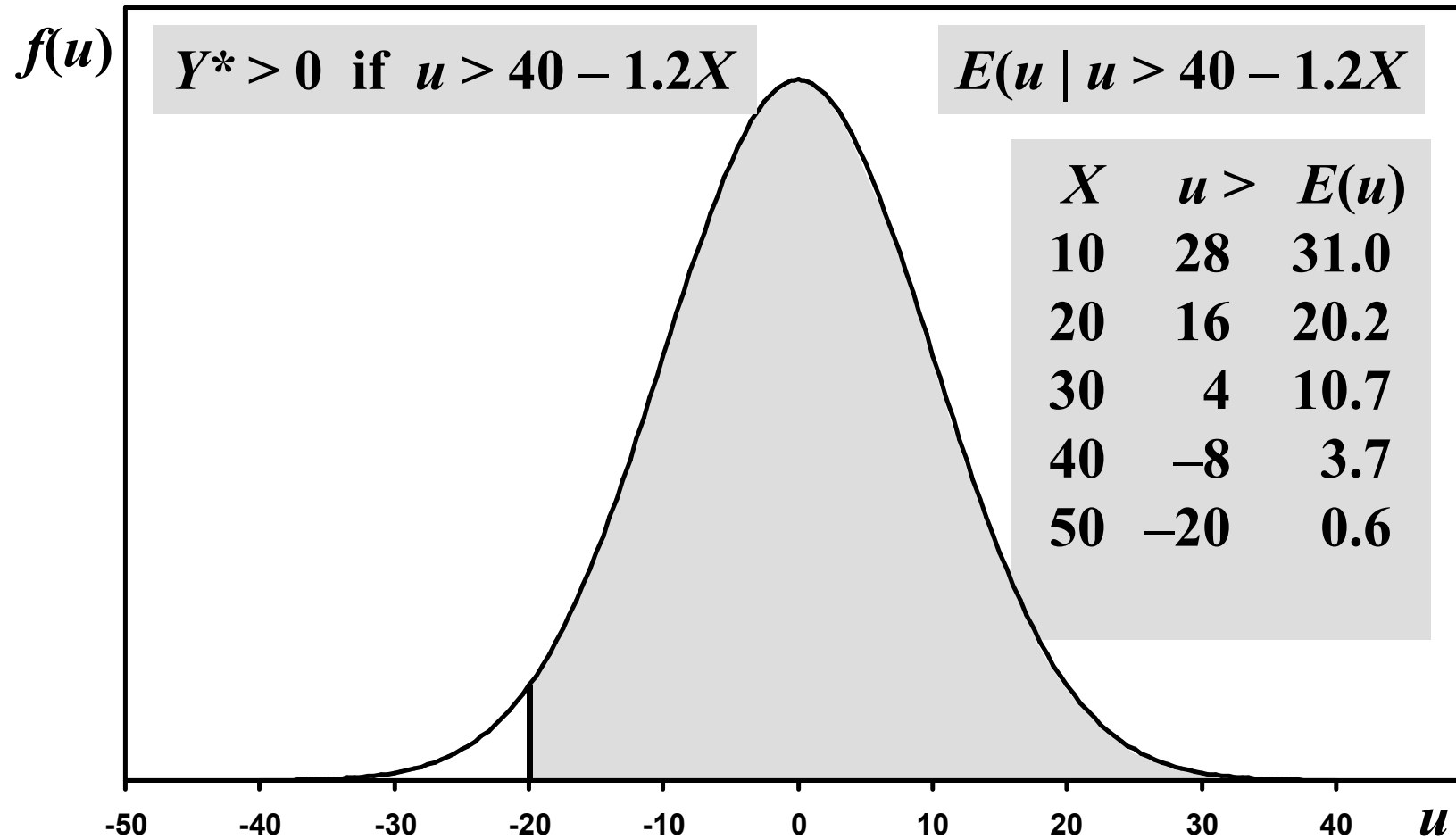
# TOBIT ANALYSIS



When  $X$  is equal to 40,  $u$  must be greater than  $-8$ . Its expected value, subject to this condition, is 3.7.

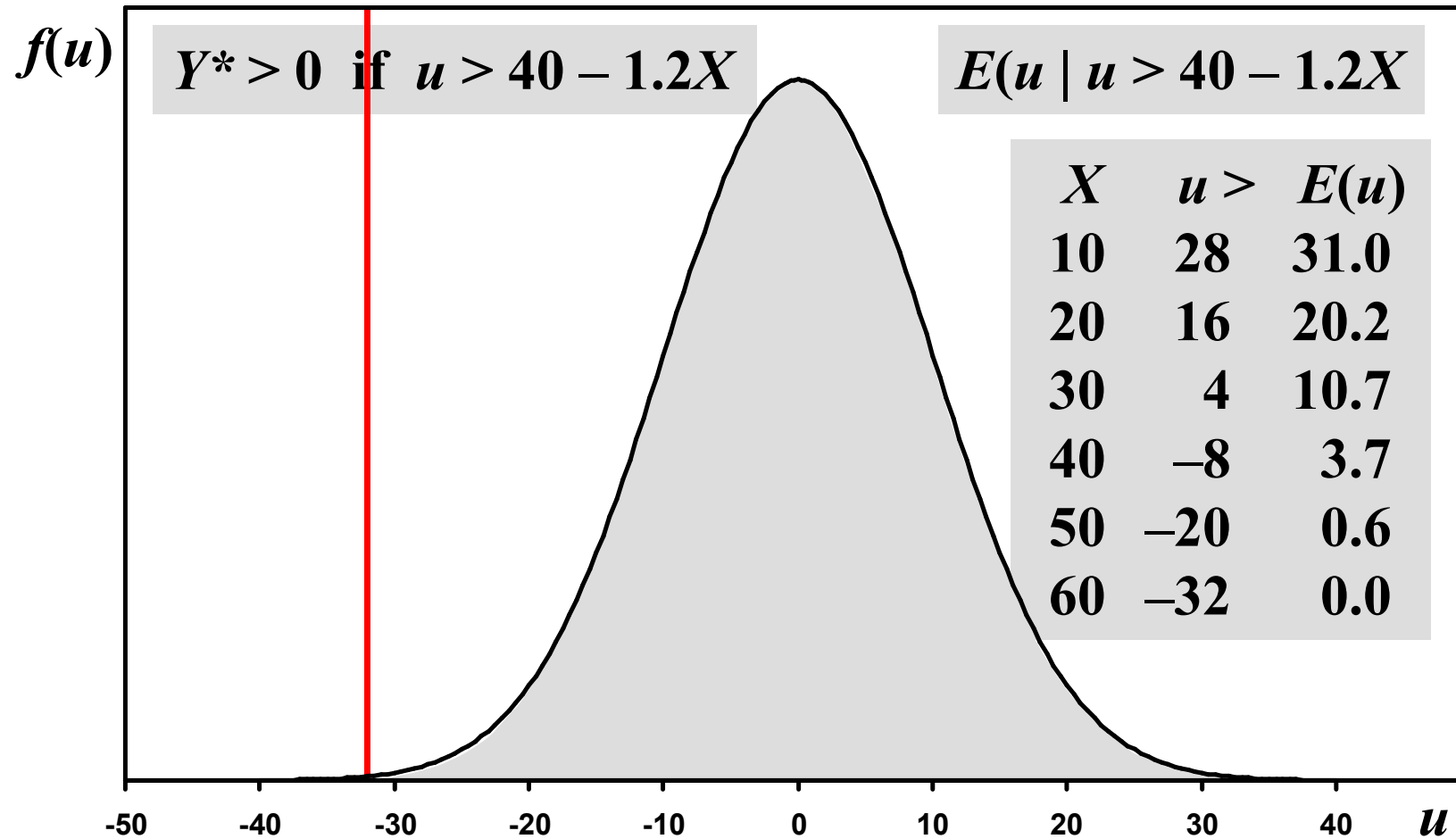


# TOBIT ANALYSIS



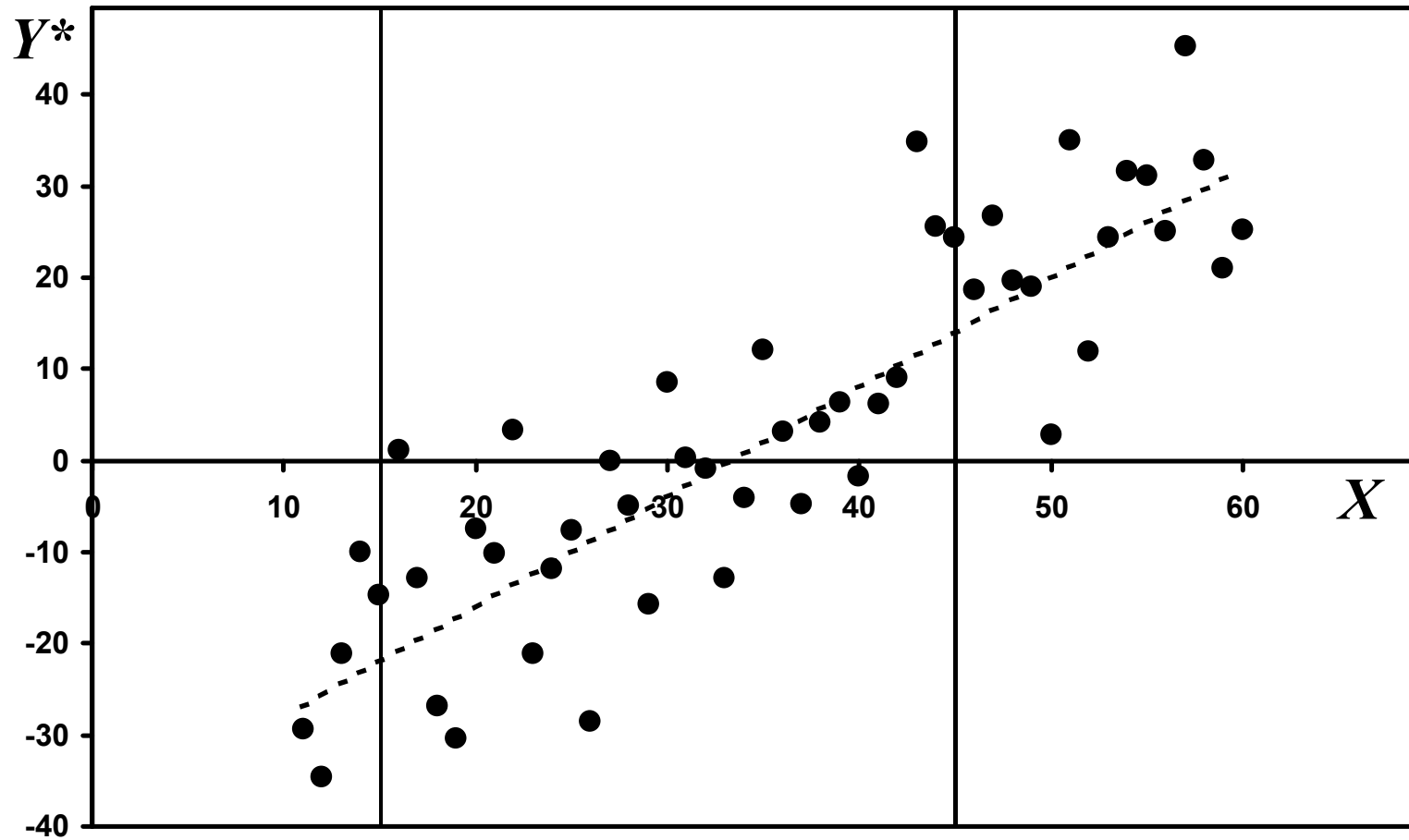
When  $X$  is equal to 50,  $u$  must be greater than  $-20$ . It will satisfy this condition nearly all the time and its conditional expected value, 0.6, is hardly any greater than its unconditional expected value, 0.

# TOBIT ANALYSIS



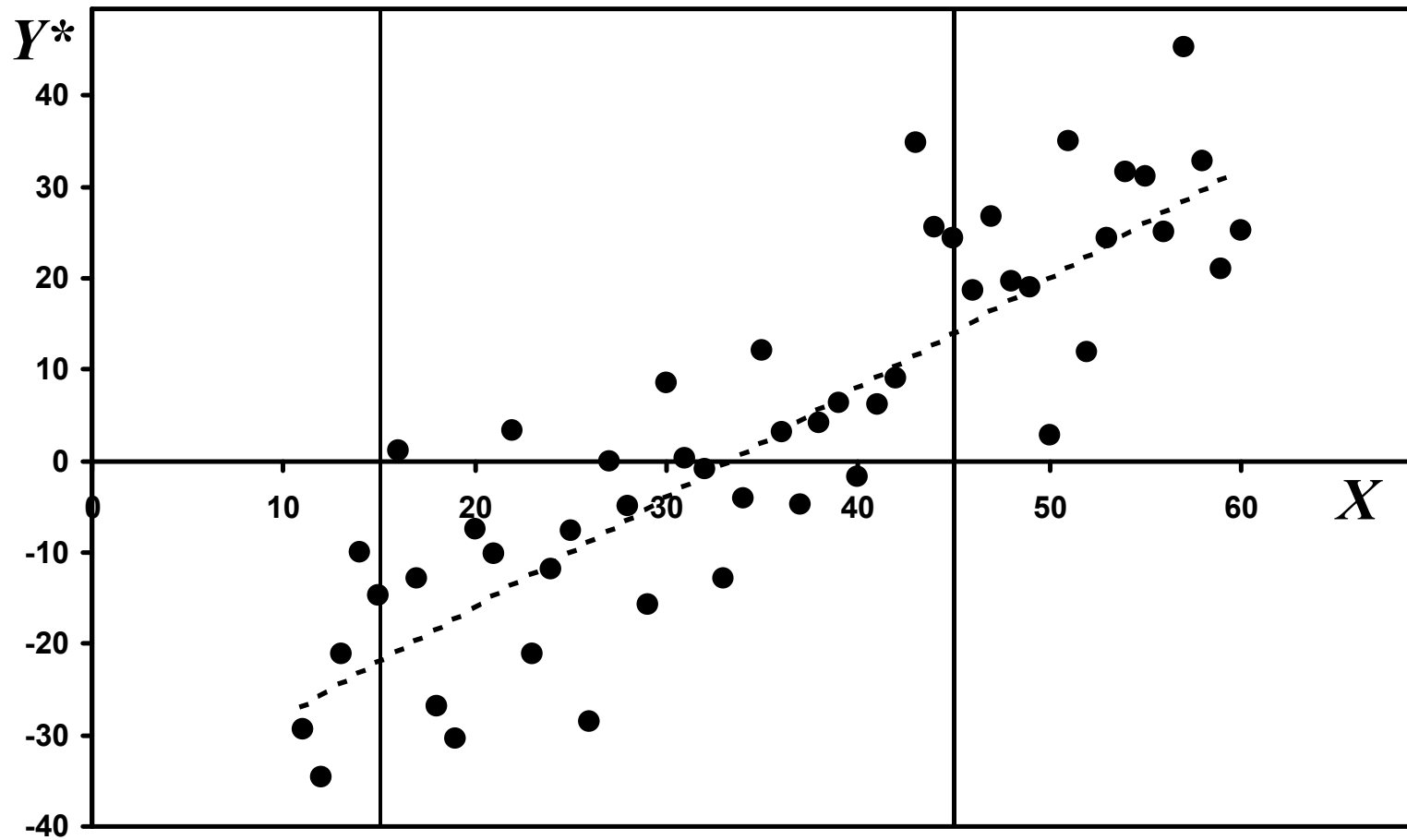
When  $X$  is 60 or higher, the condition will always be satisfied and the observation will always appear in the sample. For  $X > 60$ ,  $E(u)$  is equal to its unconditional value of 0 and so there is no negative correlation between  $X$  and  $u$ .

# TOBIT ANALYSIS



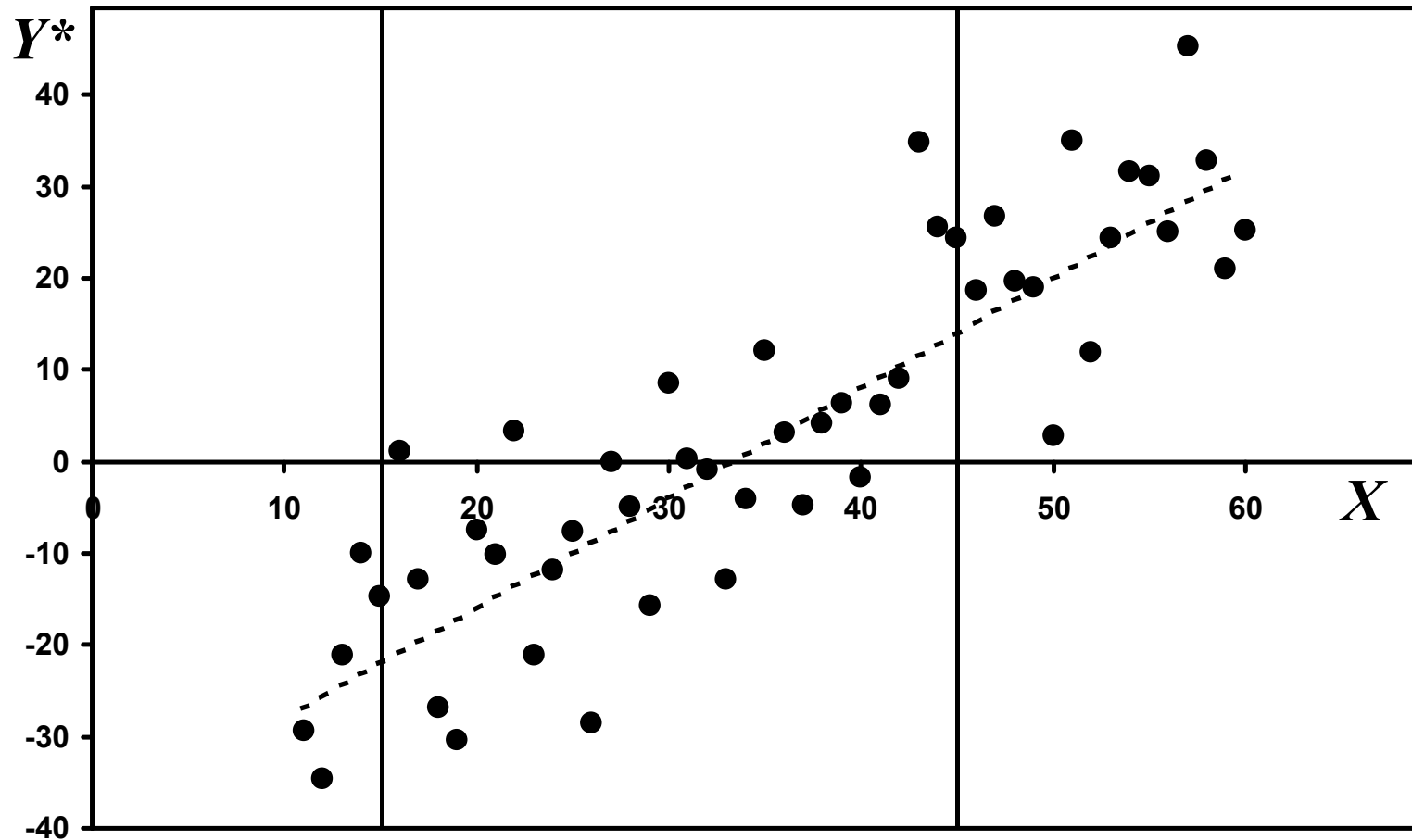
The range over which one observes a negative correlation between  $X$  and  $u$  is approximately 15 to 45. Below 15, an observation is almost certainly going to be constrained and so deleted from the sample.

# TOBIT ANALYSIS



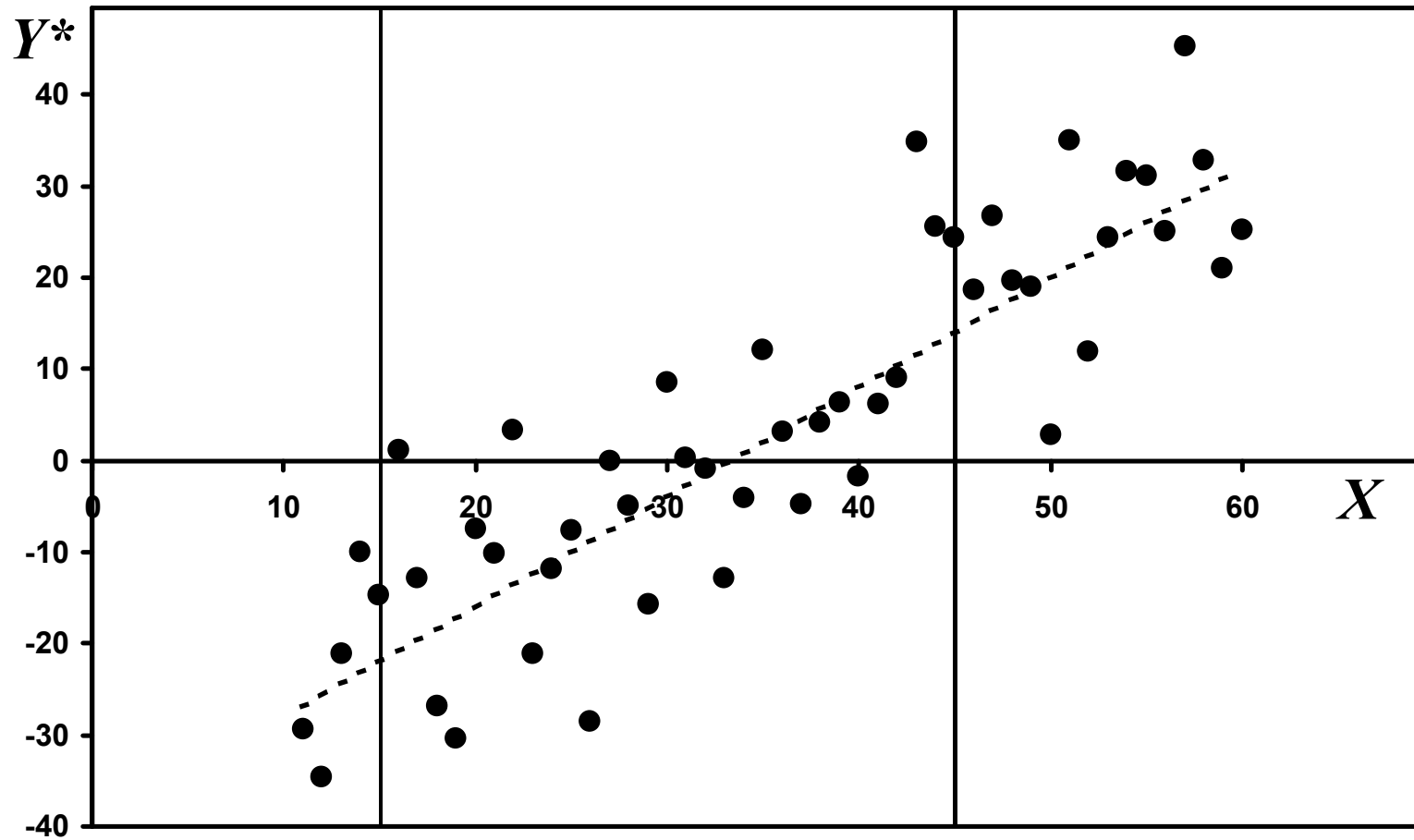
Above 45, almost all are going to appear in the sample, irrespective of the value of  $u$ .

# TOBIT ANALYSIS



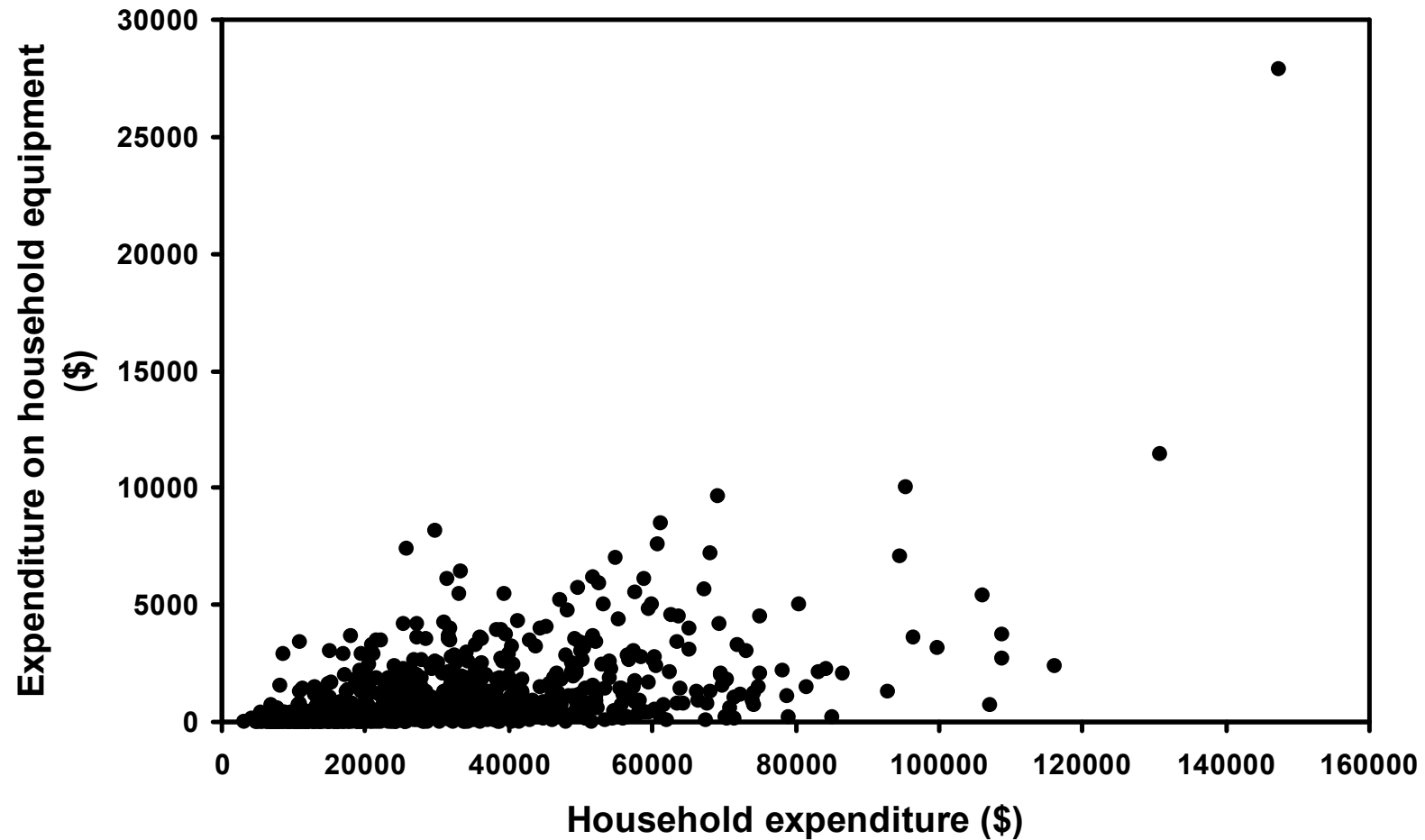
The solution to the problem is to have a hybrid model which effectively uses probit analysis to investigate why some observations have positive  $Y^*$  while others do not, and then, for those with  $Y^* > 0$ , regression analysis to quantify the relationship.

# TOBIT ANALYSIS



The model is fitted using maximum likelihood estimation. We will not be concerned with the technicalities here.

## TOBIT ANALYSIS



We will use the Consumer Expenditure Survey data set to illustrate the use of tobit analysis. The figure plots annual household expenditure on household equipment, *HEQ*, on total household expenditure, *EXP*, both measured in dollars.

## TOBIT ANALYSIS

```
. tab HEQ if HEQ<10
```

HEQ	Freq.	Percent	Cum.
0	86	89.58	89.58
3	1	1.04	90.62
4	2	2.08	92.71
6	1	1.04	93.75
7	1	1.04	94.79
8	5	5.21	100.00
Total	96	100.00	

For 86 households, *HEQ* was 0. (The tabulation has been confined to small values of *HEQ*. We are only interested in finding out how many actually had *HEQ* = 0.)



# TOBIT ANALYSIS

```
. reg HEQ EXP
```

Source	SS	df	MS			
-----+-----				Number of obs	=	869
Model	729289164	1	729289164	F( 1, 867)	=	353.91
Residual	1.7866e+09	867	2060635.12	Prob > F	=	0.0000
-----+-----				R-squared	=	0.2899
Total	2.5159e+09	868	2898456.01	Adj R-squared	=	0.2891
				Root MSE	=	1435.5
-----						
HEQ	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
EXP	.0471546	.0025065	18.813	0.000	.042235	.0520742
_cons	-397.2088	89.44449	-4.441	0.000	-572.7619	-221.6558
-----						

Here is a regression using all the observations. We anticipate that the coefficient of *EXP* is biased downwards.

## TOBIT ANALYSIS

```
. reg HEQ EXP if HEQ>0
```

Source	SS	df	MS			
-----+-----				Number of obs	=	783
Model	656349265	1	656349265	F( 1, 781)	=	291.04
Residual	1.7613e+09	781	2255219.19	Prob > F	=	0.0000
-----+-----				R-squared	=	0.2715
Total	2.4177e+09	782	3091656.59	Adj R-squared	=	0.2705
				Root MSE	=	1501.7
-----						
HEQ	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
EXP	.0467672	.0027414	17.060	0.000	.0413859	.0521485
_cons	-350.1704	101.8034	-3.440	0.001	-550.0112	-150.3296
-----						

Here is an OLS regression with the constrained observations dropped. The estimate of the slope coefficient is almost the same, just a little lower.

# TOBIT ANALYSIS

```
. tobit HEQ EXP, ll(0)
```

Tobit Estimates

Number of obs = 869  
chi2(1) = 315.41  
Prob > chi2 = 0.0000  
Pseudo R2 = 0.0223

Log Likelihood = -6911.0175

HEQ	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
EXP	.0520828	.0027023	19.273	0.000	.0467789	.0573866
_cons	-661.8156	97.95977	-6.756	0.000	-854.0813	-469.5499
_se	1521.896	38.6333			(Ancillary parameter)	

Obs. summary:           86 left-censored observations at HEQ<=0  
                  783 uncensored observations

Here is the tobit regression. The Stata command is 'tobit', followed by the dependent variable and the explanatory variables, then a comma, then 'll' and in parentheses the lower limit.

# TOBIT ANALYSIS

```
. tobit HEQ EXP, ll(0)
```

Tobit Estimates

Number of obs = 869  
 chi2(1) = 315.41  
 Prob > chi2 = 0.0000  
 Pseudo R2 = 0.0223

Log Likelihood = -6911.0175

HEQ	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
EXP	.0520828	.0027023	19.273	0.000	.0467789	.0573866
_cons	-661.8156	97.95977	-6.756	0.000	-854.0813	-469.5499
_se	1521.896	38.6333			(Ancillary parameter)	

Obs. summary: 86 left-censored observations at HEQ<=0  
 783 uncensored observations

If the dependent variable were constrained by an upper limit, we would use 'u1' instead of 'll', with the upper limit in parentheses. The method can handle lower limits and upper limits simultaneously.

## TOBIT ANALYSIS

```
. tobit HEQ EXP, ll(0)
```

HEQ	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
EXP	.0520828	.0027023	19.273	0.000	.0467789	.0573866
_cons	-661.8156	97.95977	-6.756	0.000	-854.0813	-469.5499
-----+-----						
_se	1521.896	38.6333	(Ancillary parameter)			

```
. reg HEQ EXP
```

HEQ	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
EXP	.0471546	.0025065	18.813	0.000	.042235	.0520742
_cons	-397.2088	89.44449	-4.441	0.000	-572.7619	-221.6558

```
. reg HEQ EXP if HEQ>0
```

HEQ	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
-----+-----						
EXP	.0467672	.0027414	17.060	0.000	.0413859	.0521485
_cons	-350.1704	101.8034	-3.440	0.001	-550.0112	-150.3296

We see that the coefficient of *EXP* is indeed larger in the tobit analysis, confirming the downwards bias in the OLS estimates. In this case the difference is not very great. That is because only 10 percent of the observations were constrained.

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