

Assignment 11

Truncated Regression & Tobit Models

Guideline Solution

The model

According to the following model,

$$y_{ki} = \beta_{k0} + \beta_{k1}x_i + u_{ki} \quad (1)$$

where: y_{ki} is Dependent variable, $k=1, 2, 3$.

x_i is Independent variable

u_i is Stochastic disturbance term

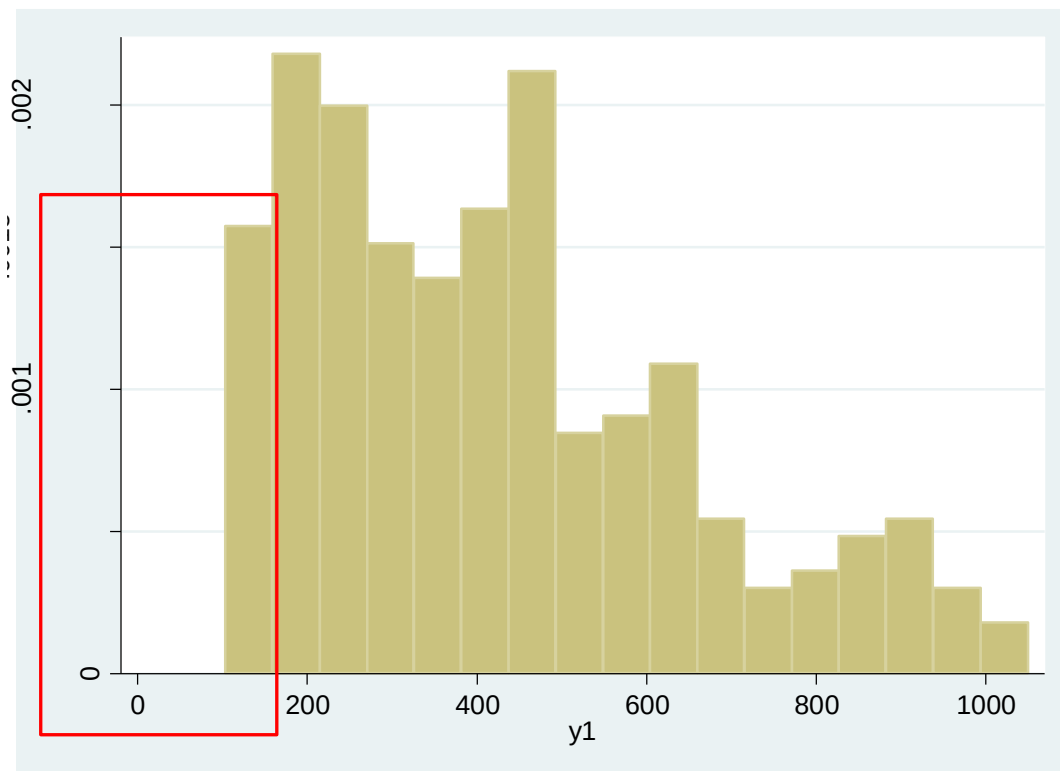
Requirements: (assign11.dta)

- 1 Plot histogram of y_{1i} , y_{2i} , y_{3i} , compute descriptive statistics of these three variables, then determine limitation of these three dependent variables.

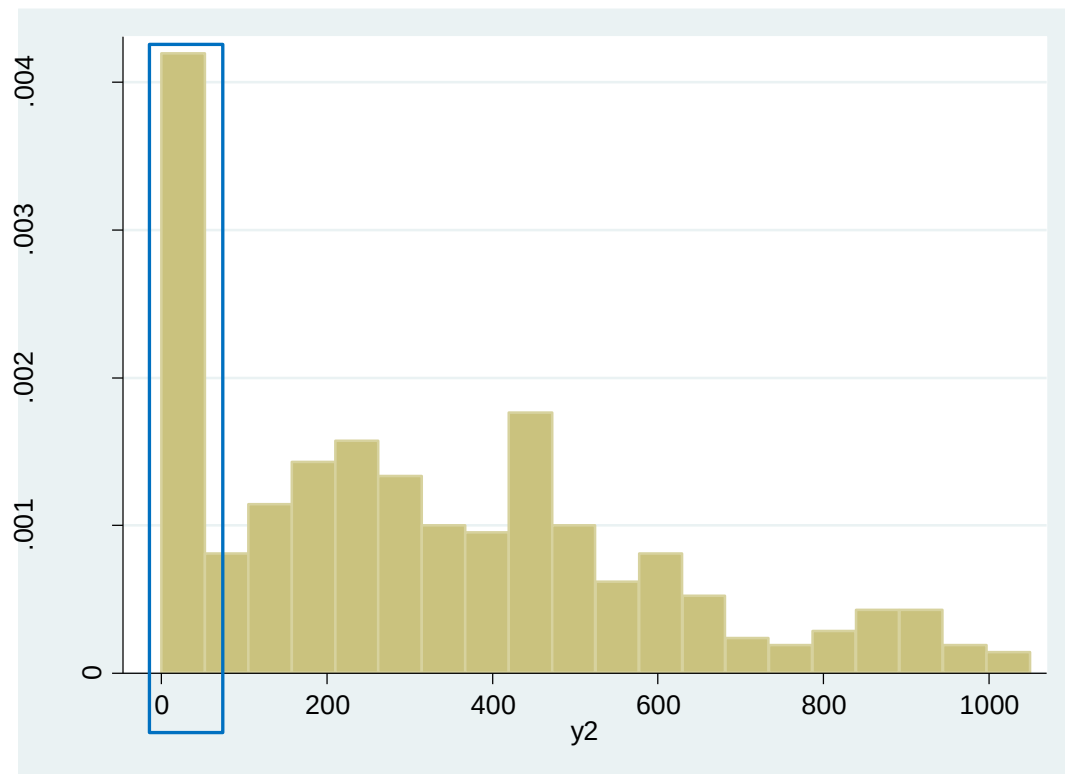
```
. sum y1 y2 y3
```

variable	Obs	Mean	Std. Dev.	Min	Max
y1	297	423.1683	227.8976	103.4663	1049.314
y2	400	317.5914	266.3419	0	1049.314
y3	400	10446.1	23186.57	-866.3348	99508.07

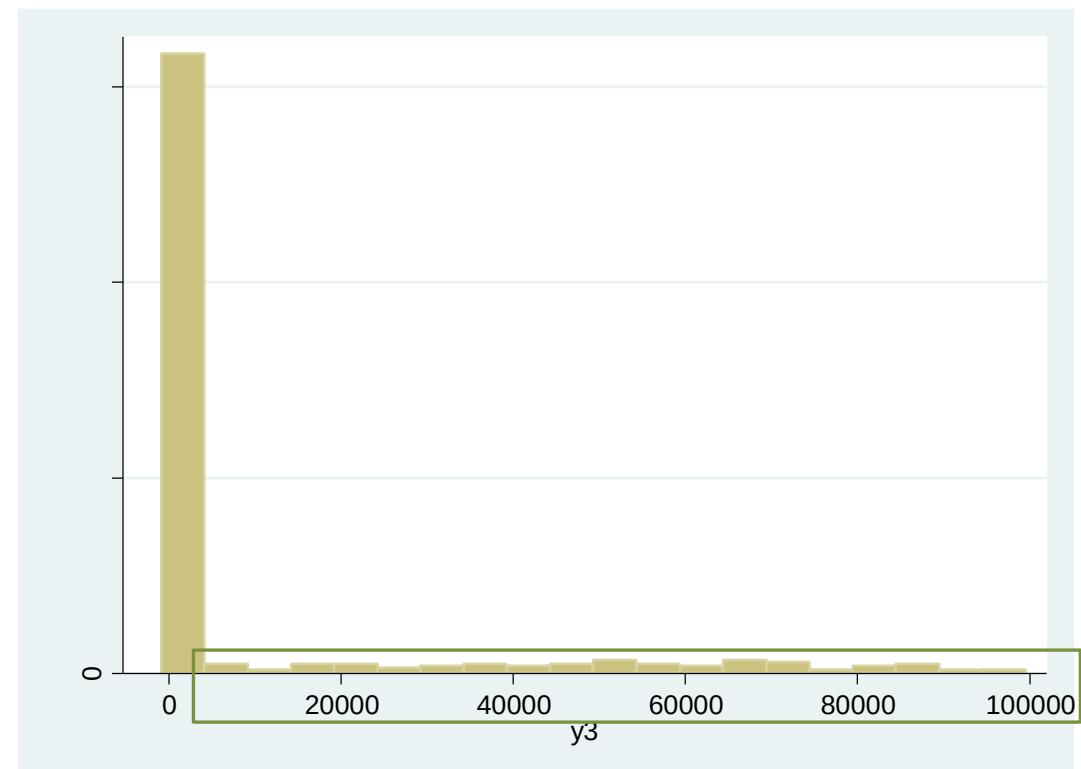
```
. histogram y1  
(bin=17, start=103.46626, width=55.638129)
```



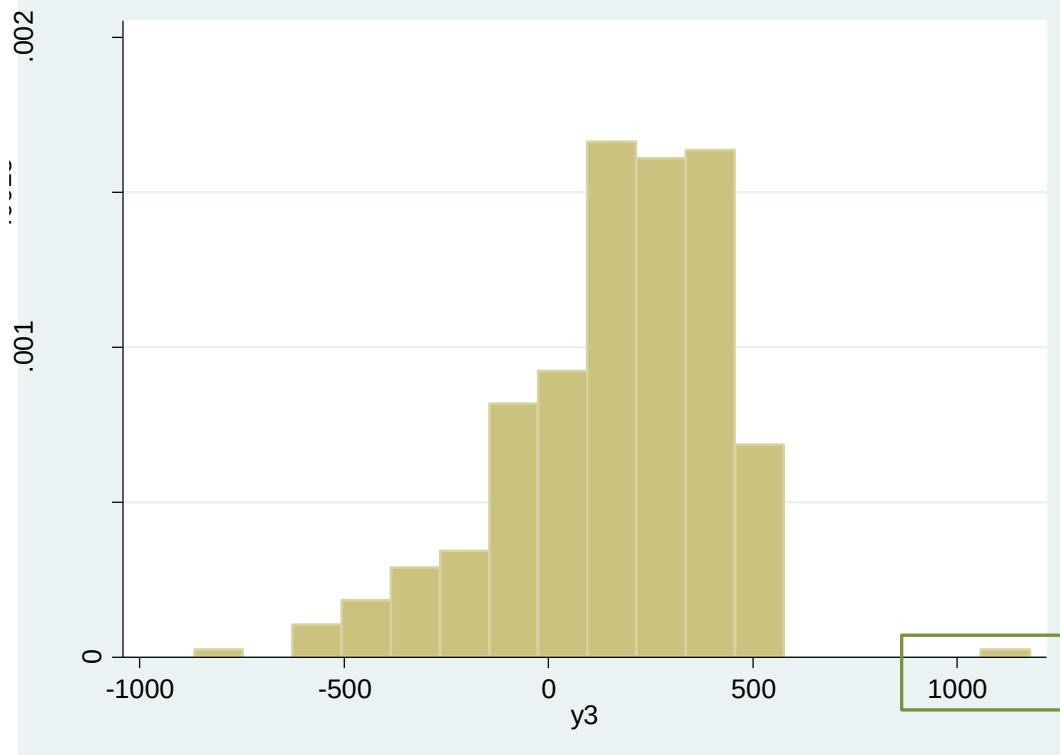
```
. histogram y2  
(bin=20, start=0, width=52.465723)
```



```
. histogram y3  
(bin=20, start=-866.33484, width=5018.7203)
```



```
. histogram y3 if y3<2000
(bin=17, start=-866.33484, width=120.20064)
```



- According to descriptive statistics (mean, sd., min., & max.) and histogram, it might be concluded that y_1 has truncated problem at around 103, y_2 has censored problem at 0, y_3 has outlier problem.

2 Estimate the model (1) for y_{1i} , y_{2i} , y_{3i} using OLS, using truncated regression model, Tobit model, determine the most appropriated models for each y_{ki} .

(1) Estimated Results of Linear Regression Model of y_1 using OLS

```
. reg y1 x
```

Source	SS	df	MS	Number of obs	=	297
Model	1431905.59	1	1431905.59	F(1, 295)	=	30.30
Residual	13941534.7	295	47259.4396	Prob > F	=	0.0000
				R-squared	=	0.0931
				Adj R-squared	=	0.0901
Total	15373440.3	296	51937.2982	Root MSE	=	217.39

y1	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	123.1693	22.37637	5.50	0.000	79.13176	167.2069
_cons	69.01677	65.56422	1.05	0.293	-60.01611	198.0496

```
. est store m_y1
```

```
. sum y1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
y1	297	423.1683	227.8976	103.4663	1049.314

```
. scalar miny1=round(r(min))
```

```
. scalar list miny1
miny1 = 103
```

Estimated Results of Truncated Regression Model

```
. truncreg y1 x, ll(miny1) nolog
(note: 0 obs. truncated)
```

```
Truncated regression
Limit:   lower =      103      Number of obs   =      297
        upper =     +inf      Wald chi2(1)    =      23.38
Log likelihood = -1973.9423      Prob > chi2     =      0.0000
```

y1	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
x	249.6062	51.61679	4.84	0.000	148.4392	350.7733
_cons	-456.6913	178.5338	-2.56	0.011	-806.6112	-106.7714
/sigma	306.4488	26.46552	11.58	0.000	254.5774	358.3203

```
. predict truncated, e(103,.)
```

```
. est store m_y1t
```

Marginal Effects

```
. mfx compute, predict(e(103,)) at(mean)
```

```
Marginal effects after truncreg
y = E(y1|y1>103) (predict, e(103,))
= 414.59149
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]		x
x	122.4108	21.825	5.61	0.000	79.6352	165.186	2.87532

```
. mfx compute, predict(e(103,)) at(median)
```

```
Marginal effects after truncreg
y = E(y1|y1>103) (predict, e(103,))
= 412.26932
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]		x
x	121.3584	21.453	5.66	0.000	79.3107	163.406	2.85627

```
. mfx compute, predict(e(103,)) at(0)
```

```
Marginal effects after truncreg
y = E(y1|y1>103) (predict, e(103,))
= 223.73689
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]		x
x	31.25194	2.26987	13.77	0.000	26.8031	35.7008	0

Test Appropriateness of Truncated Regression Model

```
. lrtest m_y1 m_y1t, force
```

```
Likelihood-ratio test      LR chi2(1) =      89.69
(Assumption: m_y1 nested in m_y1t)  Prob > chi2 =      0.0000
```

- **According to significant LR-test between linear regression model and Truncated regression model, it can be concluded that Truncated regression model is a more appropriated model in this case.**

(2) Estimated Results of Linear Regression Model of y_2 using OLS

. reg y2 x

Source	SS	df	MS	Number of obs	=	400
Model	4567087.34	1	4567087.34	F(1, 398)	=	76.58
Residual	23737174.2	398	59641.1413	Prob > F	=	0.0000
				R-squared	=	0.1614
				Adj R-squared	=	0.1592
Total	28304261.6	399	70937.9989	Root MSE	=	244.22

y2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	179.8325	20.55046	8.75	0.000	139.4315	220.2335
_cons	-179.3679	58.08821	-3.09	0.002	-293.566	-65.1698

. est store m_y2

Estimated Results of Tobit Regression Model setting lower limit at 0

. tobit y2 x, ll(0)

Tobit regression	Number of obs	=	400
	LR chi2(1)	=	73.17
	Prob > chi2	=	0.0000
Log likelihood = -2389.3077	Pseudo R2	=	0.0151

y2	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	219.1562	24.86468	8.81	0.000	170.2741	268.0383
_cons	-318.6265	70.93087	-4.49	0.000	-458.0714	-179.1816
/sigma	284.9073	11.56717			262.1671	307.6475

72 left-censored observations at $y_2 \leq 0$
328 uncensored observations
0 right-censored observations

. est store m_y2c

Marginal Effects

. mfx compute, predict(ystar(0,.)) at(mean)

Marginal effects after tobit
 $y = E(y_2 | y_2 > 0)$ (predict, ystar(0,.))
= 310.40874

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]		x
x	184.7744	20.984	8.81	0.000	143.647	225.902	2.76346

. mfx compute, predict(ystar(0,.)) at(median)

Marginal effects after tobit
 $y = E(y_2 | y_2 > 0)$ (predict, ystar(0,.))
= 308.36848

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]		x
x	184.3248	20.885	8.83	0.000	143.39	225.259	2.7524

. mfx compute, predict(ystar(0,.)) at(0)

Marginal effects after tobit
 $y = E(y_2 | y_2 > 0)$ (predict, ystar(0,.))
= 18.851247

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]		x
x	28.86472	8.50363	3.39	0.001	12.1979	45.5315	0

Test Appropriateness of Tobit Regression Model

```
. lrtest m_y2 m_y2c, force
```

Likelihood-ratio test
(Assumption: m_y2 nested in m_y2c)

LR chi2(1) = 752.97
Prob > chi2 = 0.0000

- **According to significant LR-test between linear regression model and Tobit regression model, it can be concluded that Tobit regression model is a more appropriated model in this case.**

(3) Estimated Results of Linear Regression Model of y_3 using OLS

```
. reg y3 x
```

Source	SS	df	MS	Number of obs	=	400
Model	1.3359e+10	1	1.3359e+10	F(1, 398)	=	26.43
Residual	2.0115e+11	398	505402183	Prob > F	=	0.0000
				R-squared	=	0.0623
				Adj R-squared	=	0.0599
Total	2.1451e+11	399	537616802	Root MSE	=	22481

y3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	9726.042	1891.765	5.14	0.000	6006.941	13445.14
_cons	-16431.39	5347.288	-3.07	0.002	-26943.85	-5918.932

```
. predict y3_hat  
(option xb assumed; fitted values)
```

```
. est store m_y3
```

```
. sum y3
```

Variable	Obs	Mean	Std. Dev.	Min	Max
y3	400	10446.1	23186.57	-866.3348	99508.07

Estimated Results of Linear Regression Model setting constraint only $y_3 \leq 500$

```
. reg y3 x if y3<=500
```

Source	SS	df	MS	Number of obs	=	314
Model	1748440.94	1	1748440.94	F(1, 312)	=	30.33
Residual	17984963.6	312	57644.1141	Prob > F	=	0.0000
				R-squared	=	0.0886
				Adj R-squared	=	0.0857
Total	19733404.5	313	63046.0209	Root MSE	=	240.09

y3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	130.1676	23.63496	5.51	0.000	83.66353	176.6717
_cons	-188.1423	64.52556	-2.92	0.004	-315.1025	-61.18199

```
. predict y3_hat_o  
(option xb assumed; fitted values)
```

```
. est store m_y3o
```

Estimated Results of Tobit Regression Model setting upper limit at 500

```
. tobit y3 x, ul(500) nolog
```

Tobit regression

Log likelihood = -2305.4404

Number of obs = 400
LR chi2(1) = 67.20
Prob > chi2 = 0.0000
Pseudo R2 = 0.0144

```

0 left-censored observations
314 uncensored observations
86 right-censored observations at v3 >= 500

```

```
. lrtest m_v3 m_v3o_t, force
```

```
LR chi2(1) = 4538.61
Prob > chi2 = 0.0000
```

- ```

. est table m_y1 m_y1t m_y2 m_y2c m_y3 m_y3o m_y3o_t, star(.1 .05 .01) stat(N
N cens rss ll rmse F chi2 r2 r2_a)

```

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 legend: \*  $p < .1$ ; \*\*  $p < .05$ ; \*\*\*  $p < .01$