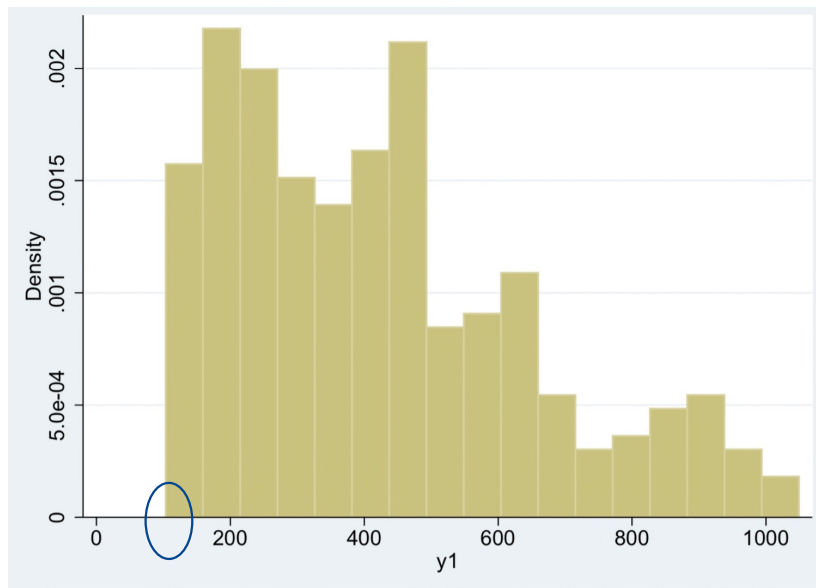
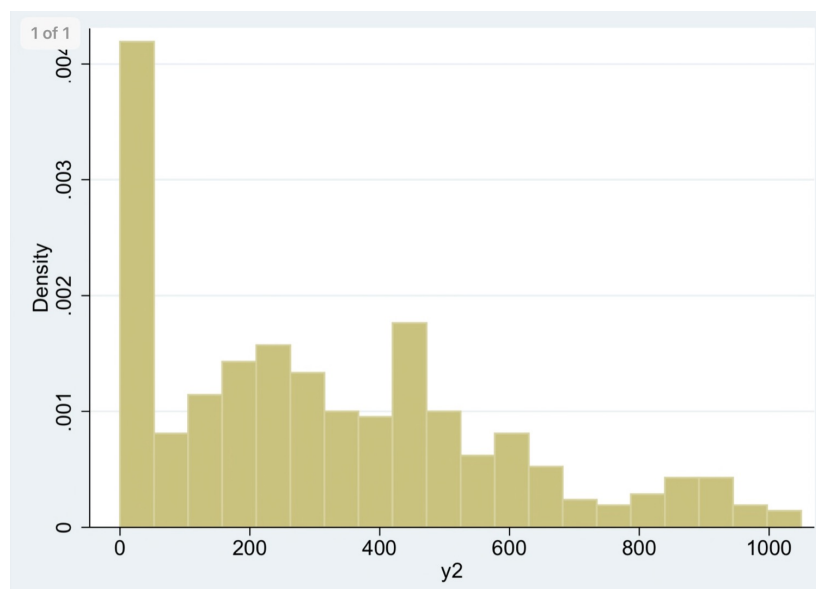


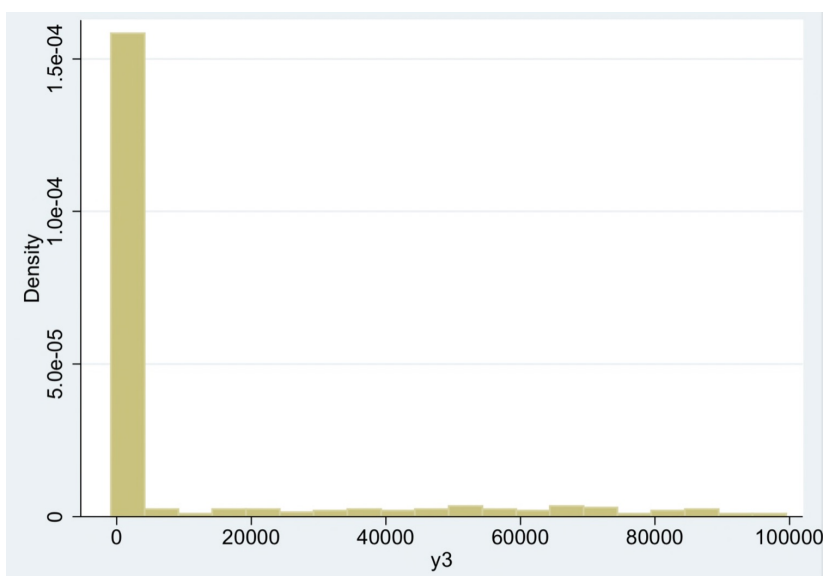
Plot histogram of y_{1i} , y_{2i} , y_{3i} , compute descriptive statistics of these three variables, then determine limitation of these three dependent variables.



y_1 : truncated at its minimum



y_2 : censored at zero



y_3 : outliers

- 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} .

```
. 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

```
. sum y1
```

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

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

```
. 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(0,.)
```

```
. est store trunc1
```

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

Marginal effects after truncreg

```
y = E(y1|y1>0) (predict, e(0,.))
= 366.96443
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x	146.2602	26.102	5.60	0.000	95.1014 197.419	2.87532

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

Marginal effects after truncreg

```
y = E(y1|y1>0) (predict, e(0,.))
= 364.18865
```

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x	145.1256	25.703	5.65	0.000	94.7479 195.503	2.85627

16 . mfx compute, predict(e(0,.)) at(0)

Marginal effects after truncreg

y = E(y1|y1>0) (predict, e(0,.))
= 134.87926

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x	37.5304	3.27981	11.44	0.000	31.1021 43.9587	0

17 . lrtest ols1 trunc1, force

Likelihood-ratio test

(Assumption: ols1 nested in trunc1)

LR chi2(1) = 89.69

Prob > chi2 = 0.0000

< 0.05 ; Truncated

18 . 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

Regression Model
is more appropriated
for y1

19 . est store ols2

20 . tobit y2 x, ll(0)

Refining starting values:

Grid node 0: log likelihood = -2400.6048

Fitting full model:

Iteration 0: log likelihood = -2400.6048

Iteration 1: log likelihood = -2389.6871

Iteration 2: log likelihood = -2389.3078

Iteration 3: log likelihood = -2389.3077

Tobit regression

Number of obs = 400

Uncensored = 328

Limits: lower = 0

Left-censored = 72

upper = +inf

Right-censored = 0

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	219.156	24.86468	8.81	0.000	170.2739 268.0382
_cons	-318.6258	70.93088	-4.49	0.000	-458.0707 -179.1808
var(e.y2)	81171.96	6591.132			69195.6 95221.18

21 . est store y2t

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

Marginal effects after tobit

y = E(y2*|y2>0) (predict, ystar(0,.))
= **310.4088**

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x	184.7743	20.984	8.81	0.000	143.647 225.902	2.76346

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

Marginal effects after tobit

y = E(y2*|y2>0) (predict, ystar(0,.))
= **308.36854**

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x	184.3247	20.885	8.83	0.000	143.39 225.259	2.7524

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

Marginal effects after tobit

y = E(y2*|y2>0) (predict, ystar(0,.))
= **18.851271**

variable	dy/dx	Std. Err.	z	P> z	[95% C.I.]	X
x	28.86475	8.52313	3.39	0.001	12.1597 45.5698	0

25 . lrtest ols2 y2t, force

Likelihood-ratio test

(Assumption: ols2 nested in y2t)

LR chi2(1) = **752.97**

Prob > chi2 = **0.0000**

Reject H₀

26 . 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

; Tobit Model
is better for γ_2

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

```
28 . est store y3
```

```
29 . sum y3
```

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

```
30 . 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

```
31 . predict y3_hat_1
(option xb assumed; fitted values)
```

```
32 . est store y3_1
```

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

Tobit regression	Number of obs	=	400
	Uncensored	=	314
Limits: lower = -inf	Left-censored	=	0
upper = 500	Right-censored	=	86
	LR chi2(1)	=	67.20
	Prob > chi2	=	0.0000
Log likelihood = -2305.4404	Pseudo R2	=	0.0144

y3	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
x	216.5213	25.84758	8.38	0.000	165.7069	267.3358
_cons	-325.0374	72.09183	-4.51	0.000	-466.7647	-183.3101
var(e.y3)	85472.85	7109.987			72578.21	100658.4

```
34 . est store y3t
```

39 . lrtest y3 y3t, force

Likelihood-ratio test
(Assumption: y3 nested in y3t)

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

Tobit Model
< 0.05 ; is better for y3

40 . est tab ols1 trunc1 ols2 y2t y3 y3_1 y3t, star(.1 .05 .01) stat(N N_cens rss ll rmse F chi2 r2 r2_a)

Variable	ols1	trunc1	ols2	y2t	y3	y3_1
— x _cons	123.16931*** 69.01677		179.83253*** -179.36788***		9726.0419*** -16431.393***	130.1676*** -188.14225***
eq1 x _cons		249.60624*** -456.6913**				
/sigma var(e.y2) var(e.y3)		306.44885***		81171.961***		
y2 x _cons				219.156*** -318.62579***		
y3 x _cons						
Statistics						
N	297	297	400	400	400	314
N_cens						
rss	13941535		23737174		2.012e+11	17984964
ll	-2018.7874	-1973.9423	-2765.7931	-2389.3077	-4574.7459	-2165.5843
rmse	217.39236		244.21536		22481.152	240.09189
F	30.298827		76.576122		26.432484	30.331647
chi2		23.384541		73.173596		
r2	.09314152		.16135688		.06227724	.08860311
r2_a	.09006742		.15924974		.05992115	.08568196

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

Variable	y3t
- x _cons	
eq1 x _cons	
/sigma var(e.y2) var(e.y3)	85472.849***
y2 x _cons	
y3 x _cons	216.52134*** -325.03736***
Statistics N N_cens rss ll rmse F chi2 r2 r2_a	400 -2305.4404 67.204135

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

```
41 . log close
    name: <unnamed>
    log: C:\Users\A\Desktop\426\426=a11.smcl
    log type: smcl
    closed on: 19 Apr 2021, 23:46:30
```

42 .