姓名：何苏燕　　学号：15320170155231　　应用微观计量 hw2

一、Using stata to show the example of “Wage Profile”

1、Fourth order polylomial

import delimited using "Wage.csv",clear

gen age2=age*age

gen age3=age*age*age

gen age4=age*age*age*age

reg wage age age2 age3 age4

```
. reg wage age age2 age3 age4

      Source |       SS           df       MS      Number of obs   =     3,000
-------------+----------------------------------   F(4, 2995)      =     70.69
       Model |   450481.49         4  112620.372   Prob > F        =    0.0000
    Residual |  4771604.22     2,995  1593.19006   R-squared       =    0.0863
-------------+----------------------------------   Adj R-squared   =    0.0850
       Total |  5222085.71     2,999  1741.27566   Root MSE        =    39.915

------------------------------------------------------------------------------
        wage |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         age |    21.2455   5.886747     3.61   0.000     9.703019    32.78797
        age2 |  -.5638585   .2061082    -2.74   0.006    -.9679865   -.1597304
        age3 |   .0068107   .0030659     2.22   0.026     .0007991    .0128222
        age4 |   -.000032   .0000164    -1.95   0.051    -.0000642    1.45e-07
       _cons |  -184.1539   60.04037    -3.07   0.002    -301.8785   -66.42941
------------------------------------------------------------------------------
```

2、Piecewise constant regression

gen cut1=1 if age >17.9 & age <=33.5

replace cut1=0 if cut1==.

gen cut2=1 if age >33.5 & age <=49

replace cut2=0 if cut2==.

gen cut3=1 if age >49 & age <=64.5

replace cut3=0 if cut3==.

gen cut4=1 if age >64.5 & age <=80.1

replace cut4=0 if cut4==.

reg wage cut1 cut2 cut3 cut4,noconstant

```
. reg wage cut1 cut2 cut3 cut4,noconstant
```

Source	SS	df	MS			
				Number of obs	=	3,000
				F(4, 2996)	=	5776.85
Model	37759456.5	4	9439864.13	Prob > F	=	0.0000
Residual	4895717.38	2,996	1634.08457	R-squared	=	0.8852
				Adj R-squared	=	0.8851
Total	42655173.9	3,000	14218.3913	Root MSE	=	40.424

wage	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
cut1	94.15839	1.476069	63.79	0.000	91.26418	97.0526
cut2	118.2119	1.080758	109.38	0.000	116.0928	120.331
cut3	117.823	1.448333	81.35	0.000	114.9831	120.6628
cut4	101.799	4.763992	21.37	0.000	92.45796	111.14

二、Using stata to show the example of “Is the CEF linear?”

1、To calculate the mean、variance and covariance of variables

import delimited using "anscombe.csv",clear

sum x1 x2 x3 x4

```
. sum x1 x2 x3 x4
```

Variable	Obs	Mean	Std. Dev.	Min	Max
x1	11	9	3.316625	4	14
x2	11	9	3.316625	4	14
x3	11	9	3.316625	4	14
x4	11	9	3.316625	8	19

sum y1 y2 y3 y4

```
. sum y1 y2 y3 y4
```

Variable	Obs	Mean	Std. Dev.	Min	Max
y1	11	7.500909	2.031568	4.26	10.84
y2	11	7.500909	2.031657	3.1	9.26
y3	11	7.5	2.030424	5.39	12.74
y4	11	7.500909	2.030579	5.25	12.5

pwcorr x1 y1

pwcorr x2 y2

pwcorr x3 y3

pwcorr x4 y4

```
. pwcorr x1 y1

             |       x1       y1
-------------+------------------
          x1 |   1.0000
          y1 |   0.8164   1.0000

. pwcorr x2 y2

             |       x2       y2
-------------+------------------
          x2 |   1.0000
          y2 |   0.8162   1.0000

. pwcorr x3 y3

             |       x3       y3
-------------+------------------
          x3 |   1.0000
          y3 |   0.8163   1.0000

. pwcorr x4 y4

             |       x4       y4
-------------+------------------
          x4 |   1.0000
          y4 |   0.8165   1.0000

.
```

2、linear regression on each dataset

twoway (scatter y1 x1) (lfit y1 x1)

graph save scatter1

twoway (scatter y2 x2) (lfit y2 x2)

graph save scatter2

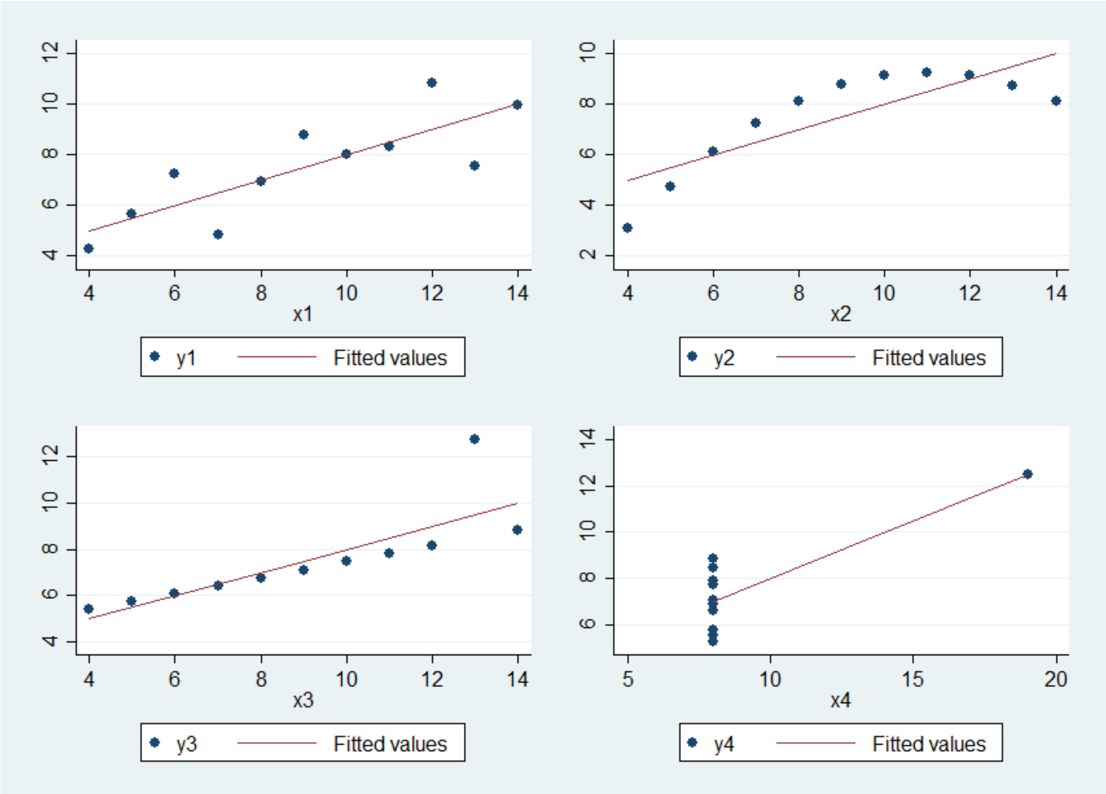
twoway (scatter y3 x3) (lfit y3 x3)

graph save scatter3

twoway (scatter y4 x4) (lfit y4 x4)

graph save scatter4

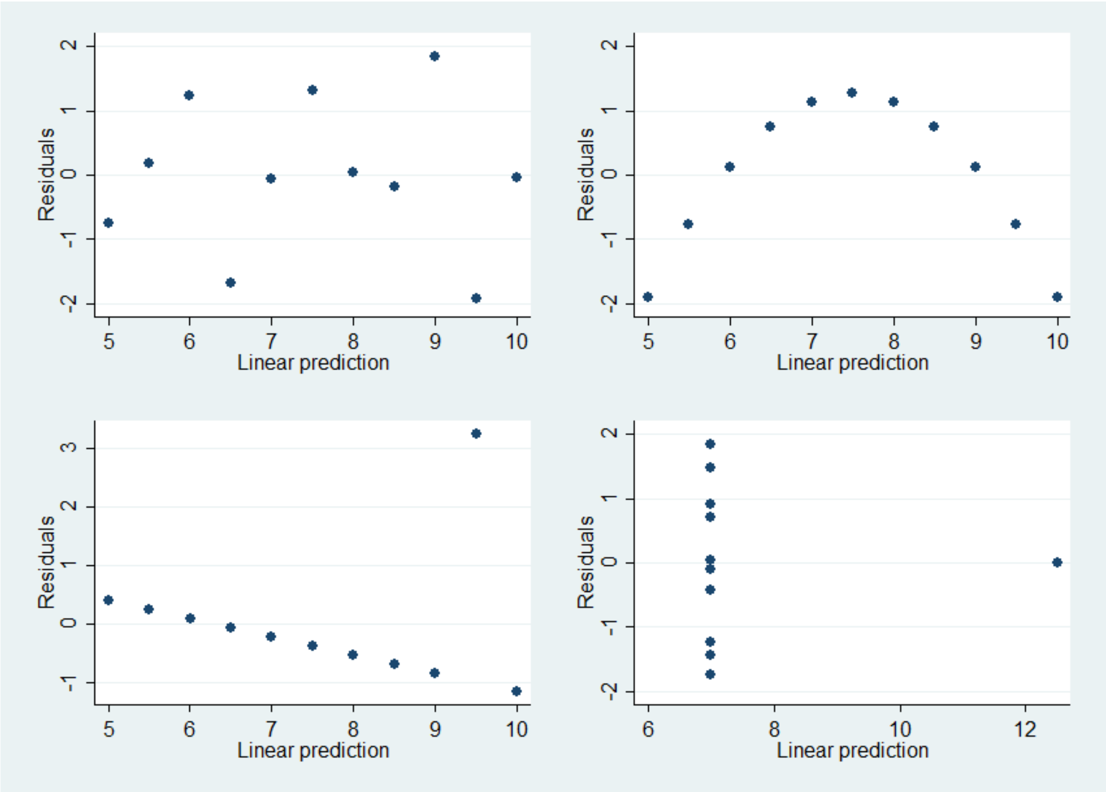
graph combine scatter1.gph scatter2.gph scatter3.gph scatter4.gph




```
reg y1 x1
predict reg1residual,r
predict reg1fitted,    xb
scatter reg1residual reg1fitted
graph save scatter5
reg y2 x2
predict reg2residual,r
predict reg2fitted,    xb
scatter reg2residual reg2fitted
graph save scatter6
reg y3 x3
predict reg3residual,r
predict reg3fitted,    xb
scatter reg3residual reg3fitted
graph save scatter7
reg y4 x4
predict reg4residual,r
predict reg4fitted,    xb
scatter reg4residual reg4fitted
```

graph save scatter8

graph combine scatter5.gph scatter6.gph scatter7.gph scatter8.gph



三、Tring bootstrap using data from Chengqiang's textbook

use grilic.dta,clear

reg lw iq s expr tenure rns smsa //homoskedastic std err

```
. reg lw iq s expr tenure rns smsa
```

Source	SS	df	MS			
				Number of obs	=	758
				F(6, 751)	=	70.39
Model	50.1363131	6	8.35605219	Prob > F	=	0.0000
Residual	89.1498367	751	.118708171	R-squared	=	0.3600
				Adj R-squared	=	0.3548
Total	139.28615	757	.183997556	Root MSE	=	.34454

lw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
iq	.0032792	.0010829	3.03	0.003	.0011532	.0054051
s	.0927874	.0066659	13.92	0.000	.0797013	.1058734
expr	.0393443	.0063057	6.24	0.000	.0269653	.0517232
tenure	.034209	.0077146	4.43	0.000	.0190641	.0493538
rns	-.0745325	.0288152	-2.59	0.010	-.1311003	-.0179647
smsa	.1367369	.0279476	4.89	0.000	.0818722	.1916016
_cons	3.895172	.1091103	35.70	0.000	3.680974	4.109369

reg lw iq s expr tenure rns smsa,vce(robust)   //robust std err

```
. reg lw iq s expr tenure rns smsa,vce(robust) //robust std err

Linear regression                               Number of obs     =        758
                                                F(6, 751)         =      71.89
                                                Prob > F          =     0.0000
                                                R-squared         =     0.3600
                                                Root MSE          =     .34454
```

lw	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
iq	.0032792	.0011321	2.90	0.004	.0010567	.0055016
s	.0927874	.0069763	13.30	0.000	.0790921	.1064826
expr	.0393443	.0066603	5.91	0.000	.0262692	.0524193
tenure	.034209	.0078957	4.33	0.000	.0187088	.0497092
rns	-.0745325	.0299772	-2.49	0.013	-.1333815	-.0156834
smsa	.1367369	.0277712	4.92	0.000	.0822186	.1912553
_cons	3.895172	.1159286	33.60	0.000	3.667589	4.122754

bootstrap,reps(400) seed(10101) nodots : reg lw iq s expr tenure rns smsa

```
. bootstrap ,reps(400) seed(10101) nodots:reg lw iq s expr tenure rns smsa

Linear regression                               Number of obs     =        758
                                                Replications      =        400
                                                Wald chi2(6)      =     395.74
                                                Prob > chi2       =     0.0000
                                                R-squared         =     0.3600
                                                Adj R-squared     =     0.3548
                                                Root MSE          =     0.3445
```

lw	Observed Coef.	Bootstrap Std. Err.	z	P>|z|	Normal-based [95% Conf.	Interval]
iq	.0032792	.0010852	3.02	0.003	.0011522	.0054061
s	.0927874	.0071037	13.06	0.000	.0788644	.1067104
expr	.0393443	.0061098	6.44	0.000	.0273693	.0513192
tenure	.034209	.0080162	4.27	0.000	.0184975	.0499204
rns	-.0745325	.0286239	-2.60	0.009	-.1306343	-.0184307
smsa	.1367369	.0276958	4.94	0.000	.0824542	.1910197
_cons	3.895172	.1194029	32.62	0.000	3.661146	4.129197

所有，我们可以看到，用 bootstrap 得到的 standard error 更接近上述回归中采用稳健标准误得到的 standard error。