

HWK 01

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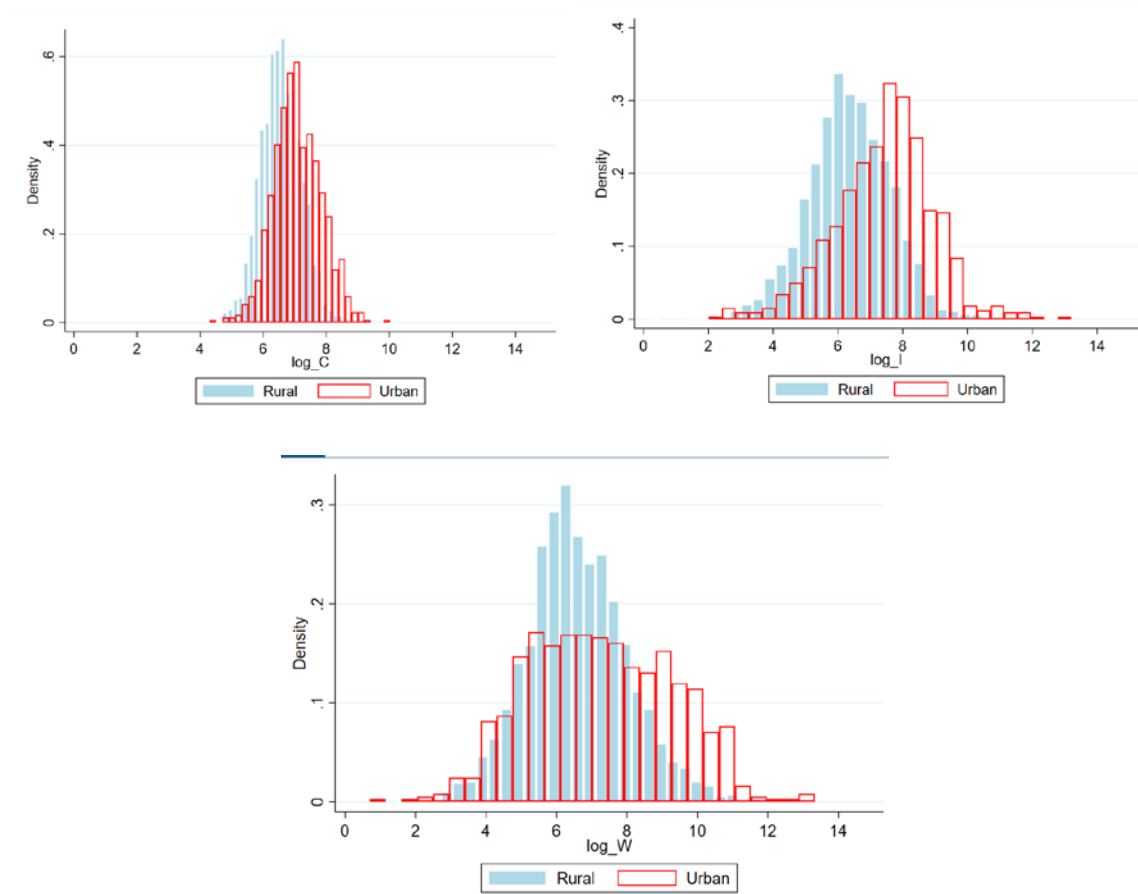
Question 1

(1).

	mean(C)	mean(I)	mean(W)
Rural	921	1403	2326
Urban	1752	5291	9964
Total	1108	2535	4323

In all 3 dimensions, the Urban is higher than Rural

(2). As we can see, they are quite similar as the slides



	var(log_C)	var(log_I)	var(log_W)
Rural	.4267483	1.728914	2.082228
Urban	.576165	2.326532	4.234638
Total	.519699	2.114658	2.733036

This is the table of variance

(3)

For total

	log_C	log_I	log_W
log_C	1.0000		
log_I	0.6166	1.0000	
log_W	0.6366	0.4422	1.0000

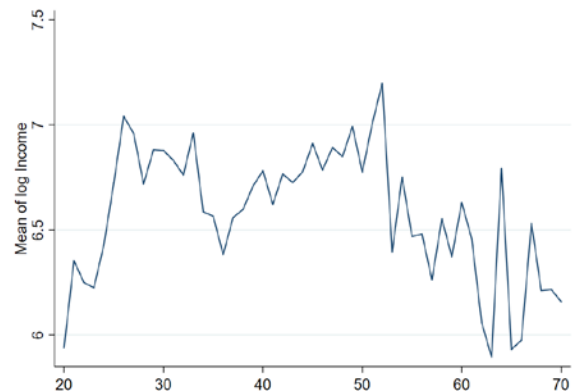
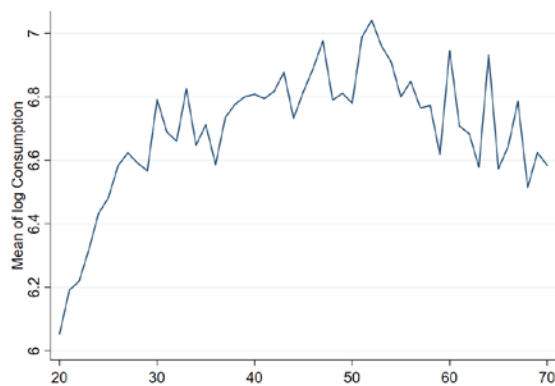
For Rural

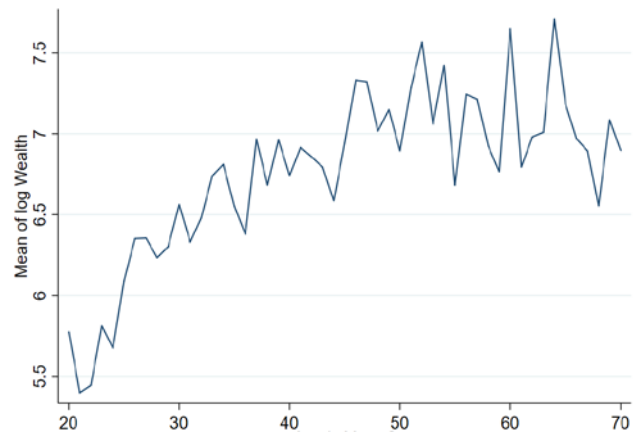
	log_C	log_I	log_W
log_C	1.0000		
log_I	0.5319	1.0000	
log_W	0.5964	0.3837	1.0000

For Urban

	log_C	log_I	log_W
log_C	1.0000		
log_I	0.6514	1.0000	
log_W	0.6701	0.4655	1.0000

(4)





(5)

Question 2

(1).

Intensive Mean

Summary statistics: mean
for variables: LS LSFam Total_LS
by categories of: urban

urban	e(LS)	e(LSFam~)	e(Total~)
Rural	639.0838	1986.935	2591.908
Urban	1464.303	1516.406	2719.536
Total	854.8534	1920.351	2609.969

Intensive Variance

Summary statistics: variance
for variables: logLS logLSFam logTotal_LS
by categories of: urban

urban	e(logLS)	e(logLS~)	e(logTo~)
Rural	1.39385	.940929	.8735892
Urban	1.377697	1.196387	1.125171
Total	1.488303	.9875084	.9087133

Extensive Mean

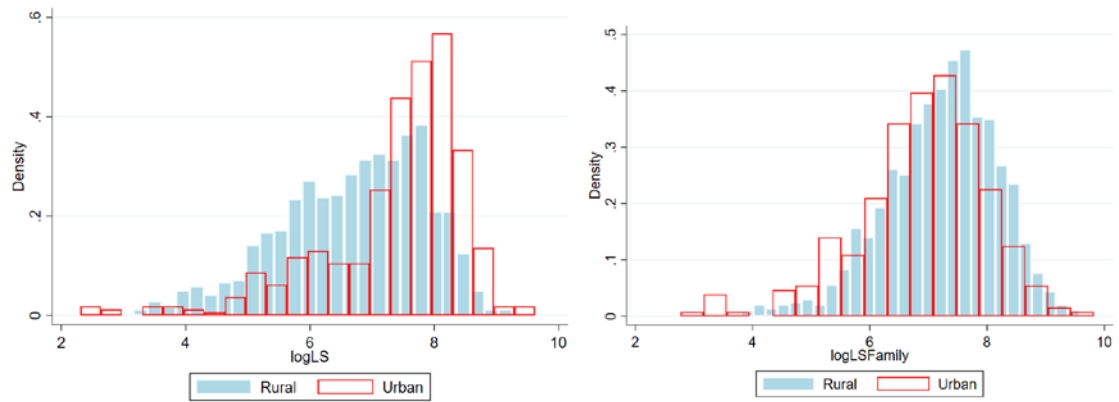
Summary statistics: mean
for variables: LS_Extensive LSFam_Extensive Total_LS_Extensive
by categories of: urban

urban	e(LS_Ex~)	e(LSFam~)	e(Total~)
Rural	46.00348	99.21807	99.52215
Urban	59.7546	97.91411	99.6319
Total	49.59897	98.87713	99.55085

Extensive Variance

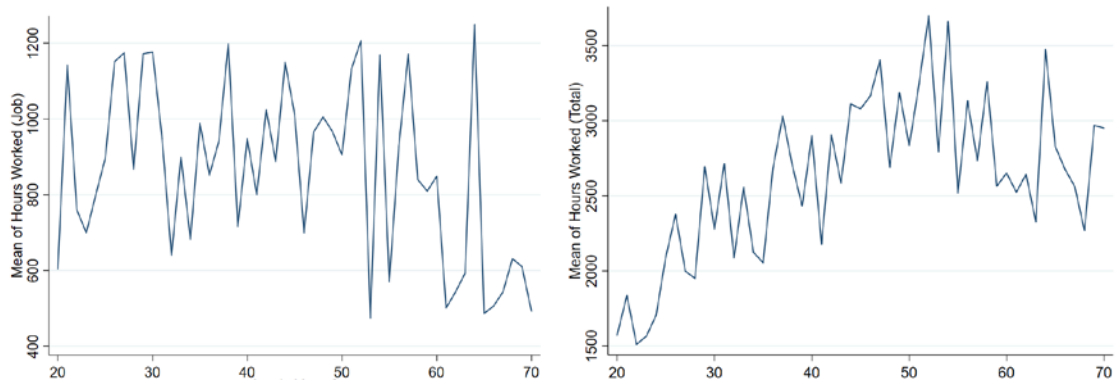
Summary statistics: variance
for variables: LS_Extensive LSFam_Extensive Total_LS_Extensive
by categories of: urban

urban	e(LS_Ex~)	e(LSFam~)	e(Total~)
Rural	2485.107	77.61518	47.57687
Urban	2407.802	204.4889	36.71937
Total	2500.641	111.0622	44.7276



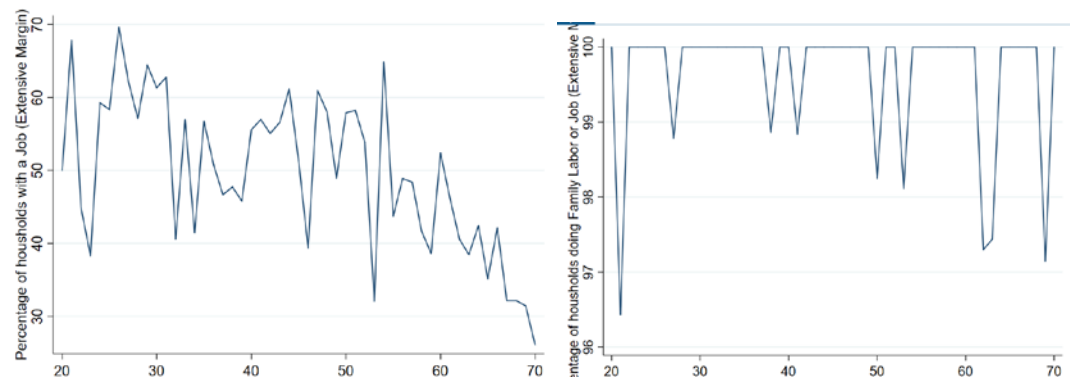
Interpretation : Maybe in rural there're more Children than in Urban.

Lifecycle Labor Supply (Intensive)



The right hand side is the total labor supply .

Lifecycle Labor Supply (Extensive)



2.2

By Women and Men

```
. estpost tabstat LS LSFfamily Total_LS, by(sex) statistics(mean)
```

Summary statistics: mean
for variables: LS LSFfamily Total_LS
by categories of: sex

sex	e(LS)	e(LSFam~)	e(Total~)
Male	891.1402	2024.738	2746.729
Female	777.122	1693.795	2313.151
Total	854.8534	1920.351	2609.969

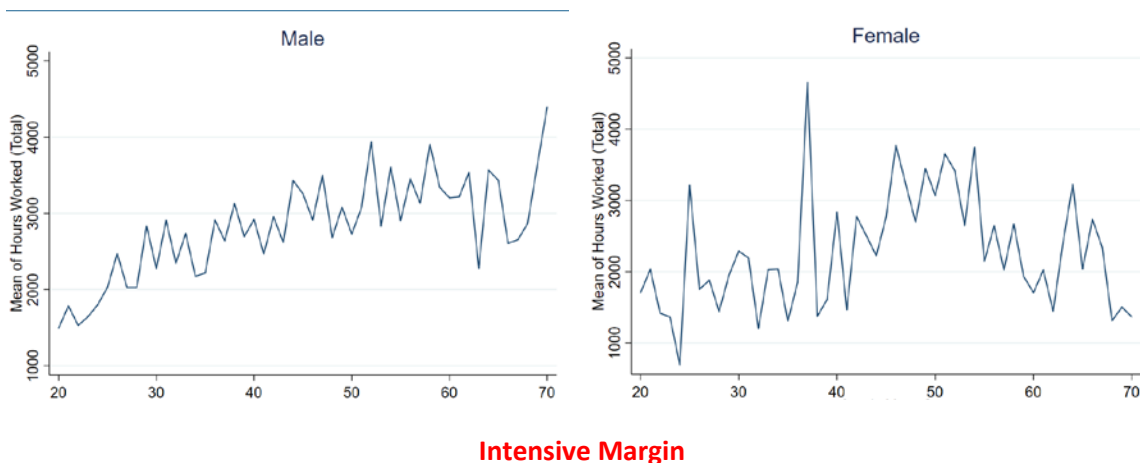
Summary statistics: mean
for variables: LS_Extensive LSFfamily_Extensive Total_LS_Extensive
by categories of: sex

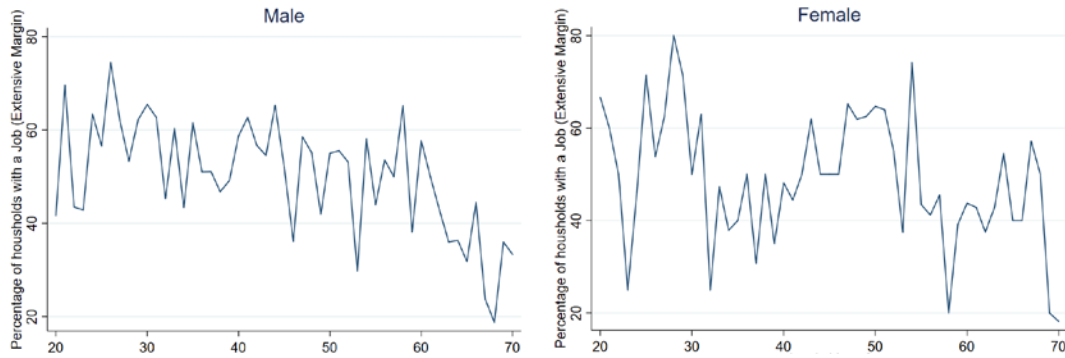
sex	e(LS_Ex~)	e(LSFam~)	e(Total~)
Male	51.38824	98.91765	99.67059
Female	45.76613	98.79032	99.29435
Total	49.59897	98.87713	99.55085

Summary statistics: variance
for variables: logLS logLSfamily logTotal_LS
by categories of: sex

sex	e(logLS)	e(logLS~)	e(logTo~)
Male	1.510737	.905207	.8157396
Female	1.435515	1.126088	1.068565
Total	1.488303	.9875084	.9087133

We find that the Labor Supply of Men is higher than Women on average in both intensive and extensive margin.





Extensive Margin

As we can see, the female fluctuates more than the Male and both go down when they becoming old

By Education

Summary statistics: mean
for variables: LS LSFamly Total_LS
by categories of: education

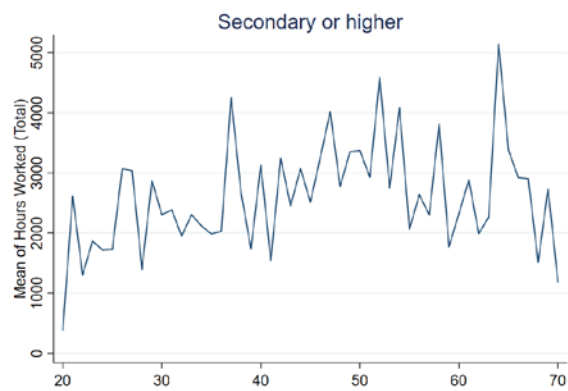
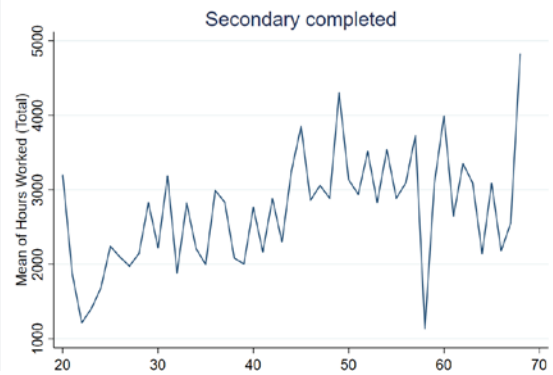
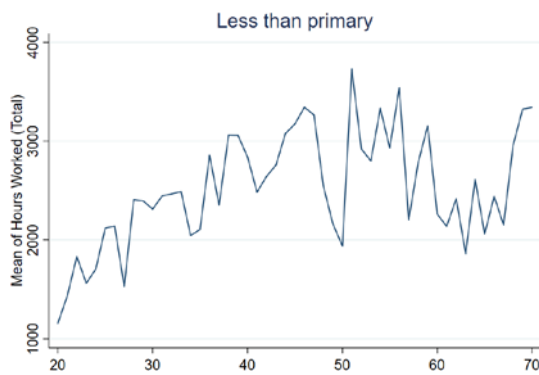
education	e(LS)	e(LSFam~)	e(Total~)
1	645.2544	2018.525	2562.887
2	825.6283	2042.342	2708.682
3	1076.051	1712.587	2591.363
Total	854.8534	1920.351	2609.969

Summary statistics: mean
for variables: LS_Extensive LSFamly_Extensive Total_LS_Extensive
by categories of: education

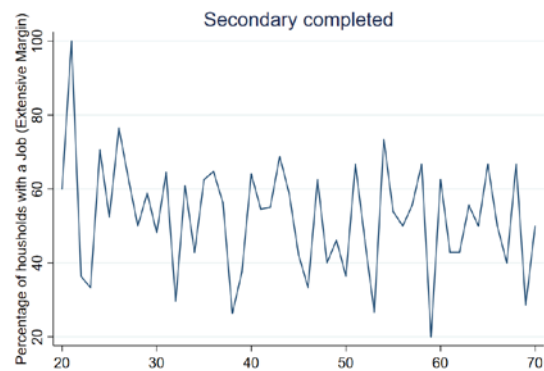
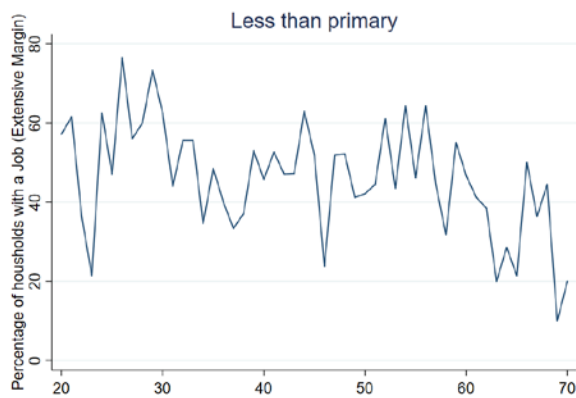
education	e(LS_Ex~)	e(LSFam~)	e(Total~)
1	45.42254	99.29577	99.3838
2	51.4393	99.1239	99.87484
3	52.36887	98.30795	99.49239
Total	49.59897	98.87713	99.55085

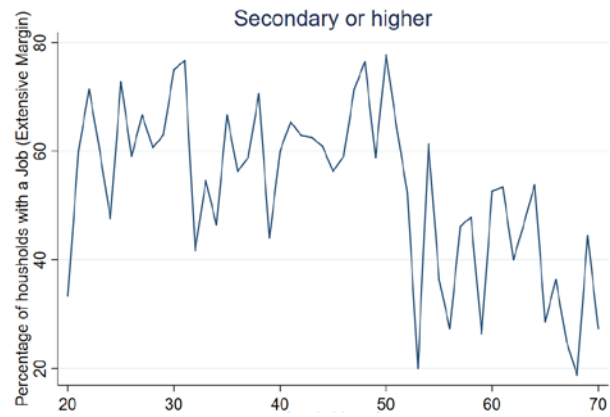
Summary statistics: variance
for variables: logLS logLSFamily logTotal_LS
by categories of: education

education	e(logLS)	e(logLS~)	e(logTo~)
1	1.619899	.9515028	.9086623
2	1.493068	.9524317	.7911067
3	1.249805	1.032474	.9934147
Total	1.488303	.9875084	.9087133



As we can see, with higher education, when they are old, they also work more hours than low educated.

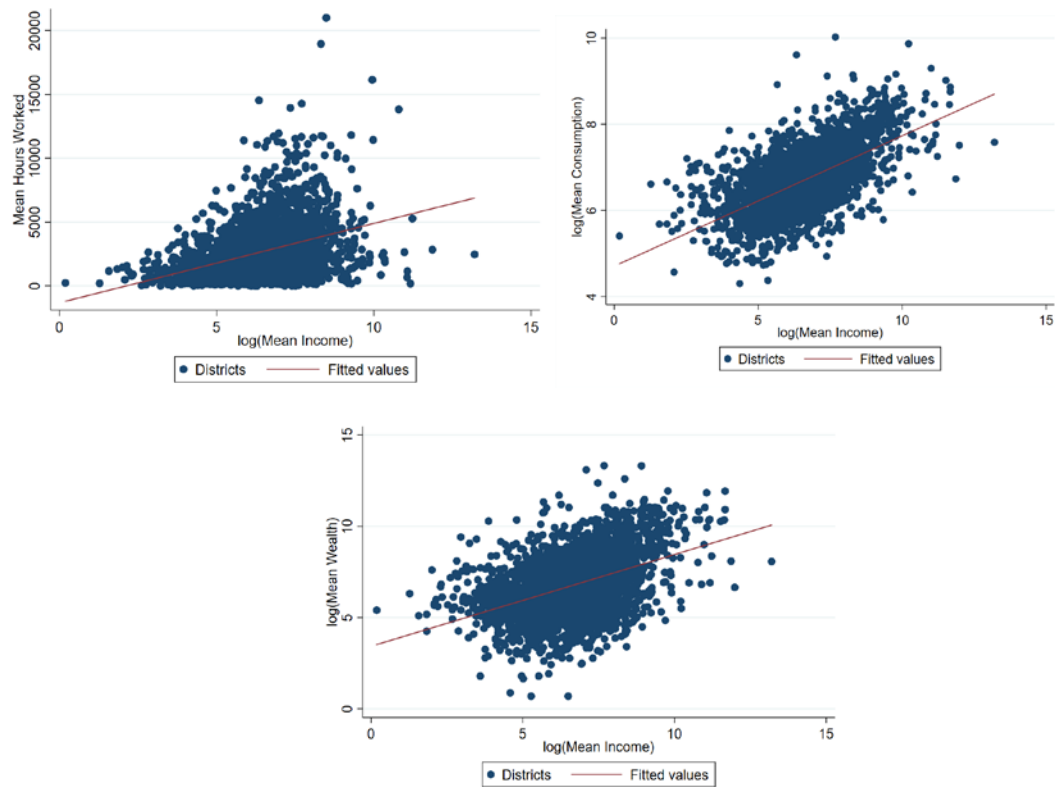




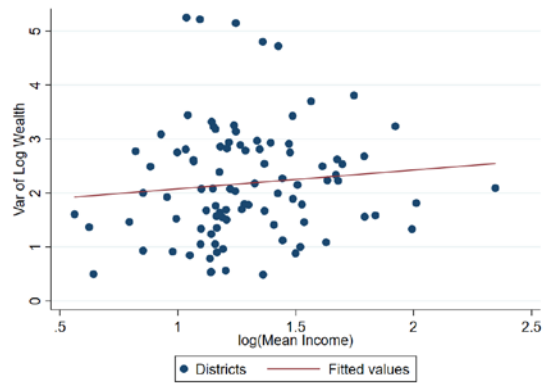
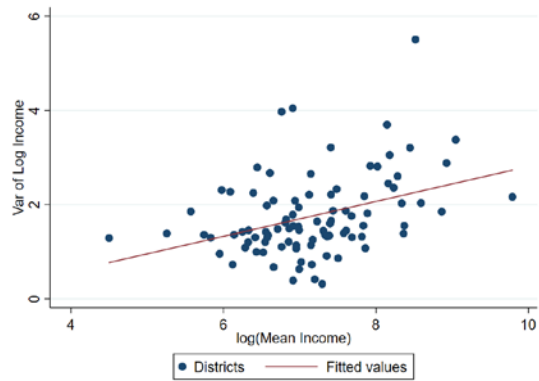
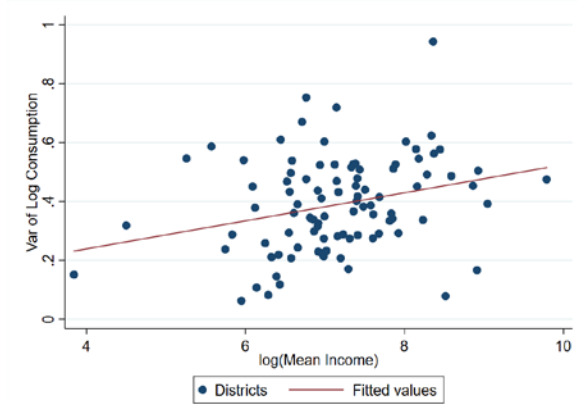
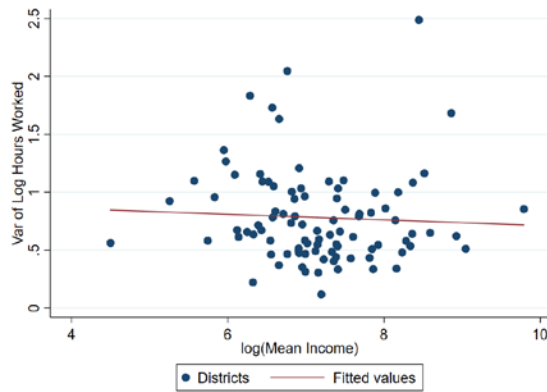
For the extensive margin, the higher educated, they have higher extensive margin in their overall life.

Question 3

(1). plot the level

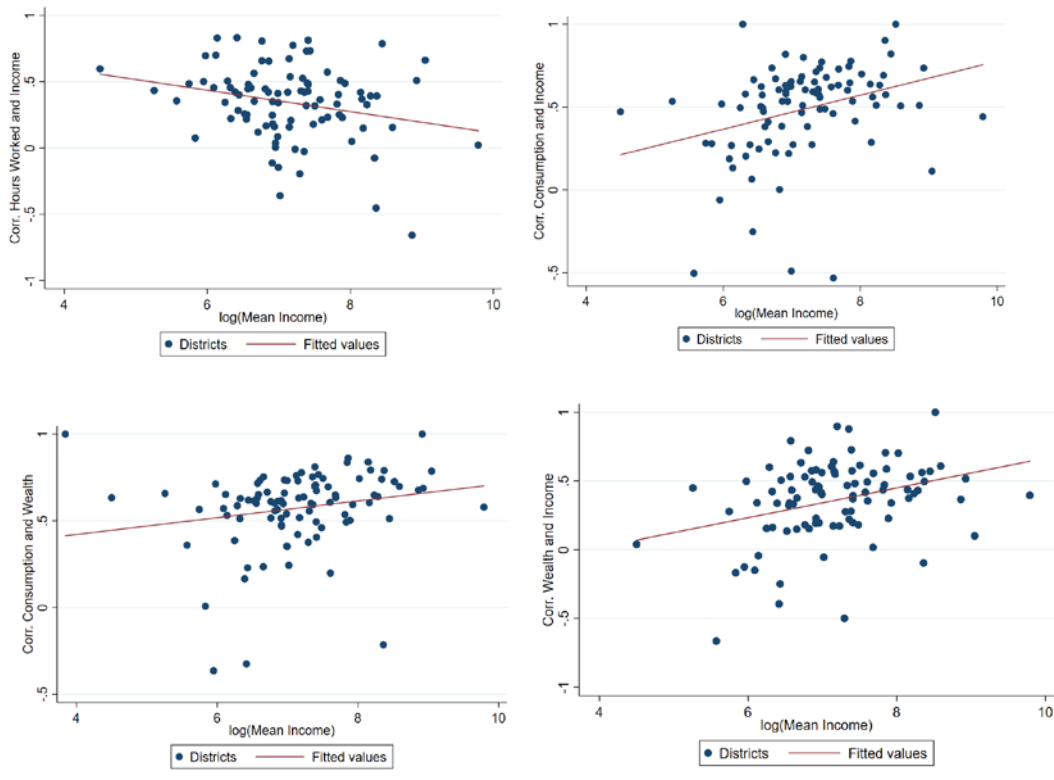


(2). Plot the inequality



We find some interesting facts, when income is higher the variance of labor supply reduce.

(3).



We find some interesting facts, when income is higher

1. the correlation between labor supply and Income becomes smaller .
2. the correlation between Consumption and Income increase a lot .
3. the correlation between Consumption and wealth are quite stable and the slop is positive but smaller .
4. the correlation between Wealth and Income increase a lot .

(4) replicate Bick et. al (2018)

```
.
. * Regressions
. xi: reg logLS log_I_Hourly age age2, vce(cluster district_code)
```

```
Linear regression              Number of obs   =       1,542
                              F(3, 97)        =         0.90
                              Prob > F         =       0.4450
                              R-squared         =       0.0024
                              Root MSE      =       1.2203
```

(Std. Err. adjusted for 98 clusters in district_code)

logLS	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
log_I_Hourly	.0382255	.1241564	0.31	0.759	-.2081906	.2846416
age	.0176957	.013441	1.32	0.191	-.0089809	.0443723
age2	-.0001972	.0001385	-1.42	0.157	-.000472	.0000775
_cons	6.515055	.3155215	20.65	0.000	5.888832	7.141278

```
. xi: reg logLS Wage age age2, vce(cluster district_code)
```

```
Linear regression              Number of obs   =       1,546
                              F(3, 98)        =         6.82
                              Prob > F         =       0.0003
                              R-squared         =       0.1404
                              Root MSE      =       1.1322
```

(Std. Err. adjusted for 99 clusters in district_code)

logLS	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
Wage	.4320455	.0986551	4.38	0.000	.2362676	.6278234
age	.0132511	.0129123	1.03	0.307	-.012373	.0388751
age2	-.0001496	.000133	-1.12	0.263	-.0004134	.0001143
_cons	6.408197	.3382289	18.95	0.000	5.736993	7.079402

```
. xi: reg logLS Wage log_I_Hourly age age2, vce(cluster district_code)
```

```
Linear regression              Number of obs   =       1,542
                              F(4, 97)        =         7.17
                              Prob > F         =       0.0000
                              R-squared         =       0.1406
                              Root MSE      =       1.133
```

(Std. Err. adjusted for 98 clusters in district_code)

logLS	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
Wage	.4337434	.1021008	4.25	0.000	.2311015	.6363853
log_I_Hourly	-.0295372	.0965627	-0.31	0.760	-.2211875	.162113
age	.0129985	.0128522	1.01	0.314	-.0125095	.0385066
age2	-.0001478	.0001328	-1.11	0.269	-.0004114	.0001159
_cons	6.437475	.3149621	20.44	0.000	5.812362	7.062587

Linear regression	Number of obs	=	1,542
	$F(2, 97)$	=	.
	Prob > F	=	.
	R-squared	=	0.2908
	Root MSE	=	1.0629

(Std. Err. adjusted for 98 clusters in district_code)

logLS	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
Wage	.3504572	.1232288	2.84	0.005	.1058822	.5950322
log_I_Hourly	.0729683	.0206076	3.54	0.001	.032068	.1138686

Interpretation:

What we care is the labor supply Elasticities.

Let's look at the coefficient on Wage, we find in the last three regressions, the number is around 0.35. and they're quite stable.