

ECO 394M Homework 3

Steven Kim

Question 1

The -6.38 Wald estimate for the weeks worked variable means the causal effect of *More than 2 children* on $E(\text{Weeks worked} | \text{More than 2 children})$ identified by the subpopulation for which by variation in *More than 2 children* is induced by a shift in sex of first two children in families with two or more children. In other words, for individuals whose fertility has been affected by their children's sex mix, *Weeks worked* is expected to decrease by 6.38 if they have more than two children. The variation of the *Weeks worked* from when the first two children's genders are the same to different divided by the variation of *More than 2 children* from when the first two children's genders are the same to different. The Z-statistic is -5.45 , which means it is statistically significant at any conventional confidence level.

Question 2

- (a) There might be other biases such as more smart students are more likely to choose to attend a choice school.
- (b) Yes, as *grant* is not correlated with u_1 .
- (c) $\text{choice} = \delta_1 + \delta_2 \text{faminc} + \pi_1 \text{grant} + v_2$ where $E(v_2) = \text{Cov}(\text{faminc}, v_2) = \text{Cov}(\text{grant}, v_2) = 0$. $\pi_1 \neq 0$ is needed for *grant* to be partially correlated with *choice*. In words, *grant* has to have an effect on *choice*.
- (d) $\text{score} = \beta_0 + \beta_1(\delta_1 + \delta_2 \text{faminc} + \pi_1 \text{grant} + v_2) + \beta_2 \text{faminc} + u_1$
 $= \beta_0 + \beta_1 \delta_1 + \beta_1 \pi_1 \text{grant} + (\beta_1 \delta_2 + \beta_2) \text{faminc} + u_1 + \beta_1 v_2$
We can see the (indirect) effect of *grant* on *score* (via *choice*).

Question 3

$$\begin{aligned}\hat{\beta} &= (X'P_zX)^{-1}X'P_zy \\ &= (X'Z(Z'Z)^{-1}Z'X)^{-1}X'Z(Z'Z)^{-1}Z'y \\ &= (Z'X)^{-1}(Z'Z)(X'Z)^{-1}X'Z(Z'Z)^{-1}Z'y \\ &= (Z'X)^{-1}Z'y\end{aligned}$$

Question 4

- (a) Since $E(u|x) = 0$, $E(xu) = E(x^2u) = E(x^3u) = 0$. Also, $\text{Corr}(x, x) \neq 0$, $\text{Corr}(x, x^2) \neq 0$, and $\text{Corr}(x, x^3) \neq 0$. Therefore, any of them each can be used as an instrument variable.
- (b) First, regress x on 1 , x^2 , and x^3 . Since there is no correlation between u and any of the instrument variables, the fitted values would be given as

$$\hat{x} = \delta_1 + \pi_1 x + \pi_2 x^2 + \pi_3 x^3$$

In the second stage, regress y on \hat{x} :

$$\begin{aligned}y &= \beta_1 + \beta_2 \hat{x} + u \\ &= \beta_1 + \beta_2(\delta_1 + \pi_1 x + \pi_2 x^2 + \pi_3 x^3) + u\end{aligned}$$

Compare this to the OLS regression of y on x, x^2, x^3 :

$$y = \alpha_1 + \alpha_2 x + \alpha_3 x^2 + \alpha_4 x^3 + u'$$

They are essentially same and we would get the same results in OLS and 2SLS.

(c) OLS (which is the same as 2SLS) minimizes the objective function

$$S(b) = \sum_i (y_i - x_i b)^2 \text{ where } x_i = [1 \quad x_i \quad x_i^2 \quad x_i^3]$$

GMM minimizes the objective function

$$S(b) = \left(\frac{1}{n} \sum_i g_i(b) \right)' \widehat{W} \left(\frac{1}{n} \sum_i g_i(b) \right) \text{ where } g_i(b) = \begin{bmatrix} (y_i - x_i b) \\ x_i(y_i - x_i b) \\ x_i^2(y_i - x_i b) \\ x_i^3(y_i - x_i b) \end{bmatrix} \text{ and } \widehat{W} = \left(\frac{1}{n} \sum_i g_i(b) g_i(b)' \right)^{-1}$$

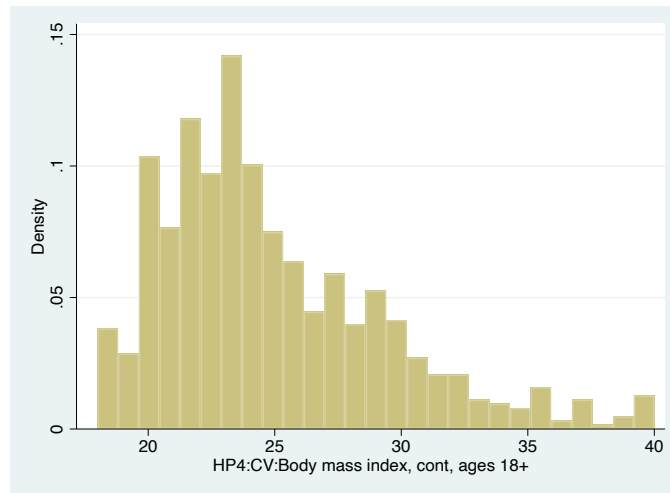
Since they minimize different objective functions, they would be different estimators. In this case, since this IV model is over-identified, GMM estimator is more efficient than the 2SLS estimator.

Question 5

- (a)
- ```
. use "children_sample.dta", clear
. keep if white & male
(1,023 observations deleted)
. tabstat bmi, statistics(p10 p25 p50 mean p75 p90)
```

| Variable | p10  | p25  | p50 | Mean     | p75  | p90   |
|----------|------|------|-----|----------|------|-------|
| bmi      | 20.2 | 21.7 | 24  | 24.91896 | 27.4 | 30.95 |

- (b)
- ```
. hist bmi
(bin=27, start=18, width=.81481481)
```



Yes, it makes sense. Mean is higher than median because of the righthand values away from the average. Other quantiles also seems right.

- (c)
- ```
. regr bmi educ age mombmi dadbmi, r
Linear regression
```

```
Number of obs = 770
F(4, 765) = 28.24
Prob > F = 0.0000
R-squared = 0.1393
Root MSE = 4.1536
```

| bmi    | Coefficient | Robust<br>std. err. | t    | P> t  | [95% conf. interval] |          |
|--------|-------------|---------------------|------|-------|----------------------|----------|
| educ   | .003787     | .1008632            | 0.04 | 0.970 | -.1942145            | .2017884 |
| age    | .2799552    | .069457             | 4.03 | 0.000 | .1436063             | .4163041 |
| mombmi | .18911      | .0310735            | 6.09 | 0.000 | .1281105             | .2501095 |
| dadbmi | .1728275    | .0402927            | 4.29 | 0.000 | .0937301             | .2519249 |
| _cons  | 9.045149    | 1.718142            | 5.26 | 0.000 | 5.672316             | 12.41798 |

The slope estimates tells us how a unit increase of each covariate would affect **bmi**, holding all others fixed.

- (d)
- ```
. sqreg bmi educ age mombmi dadbmi, reps(500)
(fitting base model)
```

```
Bootstrap replications (500)
----- 1 ----- 2 ----- 3 ----- 4 ----- 5
..... 50
..... 100
..... 150
..... 200
..... 250
..... 300
..... 350
```

```

..... 400
..... 450
..... 500
Simultaneous quantile regression          Number of obs =      770
bootstrap(500) SEs                      .50 Pseudo R2 =      0.0796

```

	bmi	Coefficient	Bootstrap std. err.	t	P> t	[95% conf. interval]	
q50							
	educ	.053927	.0916563	0.59	0.556	-.1260008	.2338548
	age	.3358445	.068398	4.91	0.000	.2015744	.4701145
	mombmi	.1315307	.0309848	4.25	0.000	.0707054	.1923561
	dadbmi	.1777306	.0440507	4.03	0.000	.0912561	.2642051
	_cons	7.681324	1.699646	4.52	0.000	4.3448	11.01785

i. A unit increase of **educ** would bring the median of **bmi** up by .053927, holding all others fixed.

ii.

```
. nlcom _b[mombmi] + _b[dadbmi], l(90)
```



```
_nl_1: _b[mombmi] + _b[dadbmi]
```

	bmi	Coefficient	Std. err.	z	P> z	[90% conf. interval]	
	_nl_1	.3092614	.0458747	6.74	0.000	.2338042	.3847185

The median of **bmi** is expected to increase by .3092614, holding all others fixed. The 90% confidence interval for this effect is given in the Stata result.

iii.

```
. sqreg bmi educ age mommbmi dadbmi, reps(500)
```



```
(fitting base model)
```

```

Bootstrap replications (500)
-----|-----|-----|-----|-----|
..... 50
..... 100
..... 150
..... 200
..... 250
..... 300
..... 350
..... 400
..... 450
..... 500
Simultaneous quantile regression          Number of obs =      770
bootstrap(500) SEs                      .50 Pseudo R2 =      0.0796

```

	bmi	Coefficient	Bootstrap std. err.	t	P> t	[95% conf. interval]	
q50							
	educ	.053927	.0957065	0.56	0.573	-.1339516	.2418056
	age	.3358445	.069755	4.81	0.000	.1989106	.4727784
	mombmi	.1315307	.0303472	4.33	0.000	.071957	.1911045
	dadbmi	.1777306	.0452244	3.93	0.000	.088952	.2665092
	_cons	7.681324	1.726007	4.45	0.000	4.293052	11.0696

The standard errors and z-statistics are slightly different because it is from different bootstrap samples than before.

(e)

```
. sqreg bmi educ age mommbmi dadbmi, q(.1 .25 .5 .75 .90) reps(500)
```



```
(fitting base model)
```

```

Bootstrap replications (500)
-----|-----|-----|-----|-----|
..... 50
..... 100
..... 150
..... 200
..... 250
..... 300

```

```

..... 350
..... 400
..... 450
..... 500
Simultaneous quantile regression      Number of obs =      770
bootstrap(500) SEs                  .10 Pseudo R2 =      0.0478
                                      .25 Pseudo R2 =      0.0771
                                      .50 Pseudo R2 =      0.0796
                                      .75 Pseudo R2 =      0.0755
                                      .90 Pseudo R2 =      0.1118

```

	bmi	Coefficient	Bootstrap std. err.	t	P> t	[95% conf. interval]	
q10							
	educ	.0772834	.1201185	0.64	0.520	-.1585175	.3130843
	age	.1946482	.0705716	2.76	0.006	.0561113	.3331851
	mombmi	.0804205	.0357001	2.25	0.025	.0103386	.1505023
	dadbmi	.1088267	.0340647	3.19	0.001	.0419554	.175698
	_cons	10.43543	1.834004	5.69	0.000	6.835156	14.03571
q25							
	educ	.0720729	.1145663	0.63	0.529	-.1528287	.2969745
	age	.2089615	.0737352	2.83	0.005	.0642142	.3537088
	mombmi	.1358798	.0308052	4.41	0.000	.075407	.1963527
	dadbmi	.1055299	.0388365	2.72	0.007	.0292911	.1817687
	_cons	10.02518	1.713144	5.85	0.000	6.662158	13.3882
q50							
	educ	.053927	.0969542	0.56	0.578	-.136401	.2442549
	age	.3358445	.0710474	4.73	0.000	.1963735	.4753155
	mombmi	.1315307	.0314753	4.18	0.000	.0697426	.1933189
	dadbmi	.1777306	.0457923	3.88	0.000	.0878371	.2676242
	_cons	7.681324	1.743933	4.40	0.000	4.257861	11.10479
q75							
	educ	.042771	.1969077	0.22	0.828	-.3437726	.4293146
	age	.3557238	.108574	3.28	0.001	.1425855	.5688622
	mombmi	.2982242	.072172	4.13	0.000	.1565455	.4399029
	dadbmi	.216229	.1000768	2.16	0.031	.0197713	.4126867
	_cons	5.228177	2.998677	1.74	0.082	-.6584344	11.11479
q90							
	educ	-.1577382	.2437446	-0.65	0.518	-.6362258	.3207494
	age	.3642897	.1732562	2.10	0.036	.0241757	.7044037
	mombmi	.3438461	.0715972	4.80	0.000	.2032958	.4843964
	dadbmi	.2529488	.0793759	3.19	0.001	.0971284	.4087691
	_cons	8.846463	5.218547	1.70	0.090	-1.397909	19.09083

- i. The slope estimate of **educ** becomes negative for q90.
- ii. Yes, it looks the original linear regression had heteroskedastic errors. It is obvious because if errors were homoskedastic, the slope estimates of any covariate in the quantile regression should be consistent over different τ values.

```

iii.      . testnl [q10]_b[age]=[q25]_b[age]=[q50]_b[age]=[q75]_b[age]=[q90]_b[age]
          (1)  [q10]_b[age] = [q25]_b[age]
          (2)  [q10]_b[age] = [q50]_b[age]
          (3)  [q10]_b[age] = [q75]_b[age]
          (4)  [q10]_b[age] = [q90]_b[age]
              chi2(4) =      4.16
              Prob > chi2 =      0.3848

```

It is 0.3848.

```

iv.      . testnl ([q50]_b[mombmi] = [q90]_b[mombmi]) ([q50]_b[dadbmi] = [q90]_b[dadbmi])
          (1)  [q50]_b[mombmi] = [q90]_b[mombmi]
          (2)  [q50]_b[dadbmi] = [q90]_b[dadbmi]
              chi2(2) =      10.89
              Prob > chi2 =      0.0043

```

P-value is 0.0043.

```

V. . preserve
. collapse (mean) educ age mombmi dadbmi
. tempfile means
. save `means'
file /var/folders/sl/twzsfyy90bq0k_r245410_100000gn/T/S_27975.000004 saved as
.dta format
. restore
. append using `means'
(variable educ was byte, now float to accommodate using data's values)
(variable age was byte, now float to accommodate using data's values)
. sqreg bmi educ age mombmi dadbmi, q(.1 .25 .5 .75 .90) reps(500)
(fitting base model)
Bootstrap replications (500)
----- 1 ----- 2 ----- 3 ----- 4 ----- 5
..... 50
..... 100
..... 150
..... 200
..... 250
..... 300
..... 350
..... 400
..... 450
..... 500
Simultaneous quantile regression                               Number of obs =       770
bootstrap(500) SEs                                           .10 Pseudo R2 =       0.0478
                                                             .25 Pseudo R2 =       0.0771
                                                             .50 Pseudo R2 =       0.0796
                                                             .75 Pseudo R2 =       0.0755
                                                             .90 Pseudo R2 =       0.1118

```

	bmi	Coefficient	Bootstrap std. err.	t	P> t	[95% conf. interval]	
q10							
	educ	.0772834	.1156081	0.67	0.504	-.1496634	.3042303
	age	.1946482	.0685983	2.84	0.005	.059985	.3293114
	mombmi	.0804205	.036183	2.22	0.027	.0093906	.1514503
	dadbmi	.1088267	.0331613	3.28	0.001	.0437288	.1739246
	_cons	10.43543	1.652902	6.31	0.000	7.190673	13.6802
q25							
	educ	.0720729	.1169336	0.62	0.538	-.1574759	.3016218
	age	.2089615	.0706963	2.96	0.003	.0701797	.3477433
	mombmi	.1358798	.0303327	4.48	0.000	.0763346	.1954251
	dadbmi	.1055299	.0386207	2.73	0.006	.0297147	.1813451
	_cons	10.02518	1.765514	5.68	0.000	6.559353	13.49101
q50							
	educ	.053927	.0962937	0.56	0.576	-.1351042	.2429582
	age	.3358445	.0735369	4.57	0.000	.1914864	.4802026
	mombmi	.1315307	.0319572	4.12	0.000	.0687965	.194265
	dadbmi	.1777306	.0441134	4.03	0.000	.0911329	.2643283
	_cons	7.681324	1.728408	4.44	0.000	4.288337	11.07431
q75							
	educ	.042771	.1878694	0.23	0.820	-.3260297	.4115717
	age	.3557238	.1167391	3.05	0.002	.1265568	.5848909
	mombmi	.2982242	.0701453	4.25	0.000	.1605241	.4359243
	dadbmi	.216229	.0994086	2.18	0.030	.021083	.411375
	_cons	5.228177	2.928817	1.79	0.075	-.5212944	10.97765
q90							
	educ	-.1577382	.2577391	-0.61	0.541	-.663698	.3482216
	age	.3642897	.1776034	2.05	0.041	.0156419	.7129376
	mombmi	.3438461	.0691785	4.97	0.000	.208044	.4796482
	dadbmi	.2529488	.0769468	3.29	0.001	.1018968	.4040007
	_cons	8.846463	5.13658	1.72	0.085	-1.237002	18.92993

```

. predict q10bmihat, equation(#1)
(option xb assumed; fitted values)
. predict q90bmihat, equation(#5)

```

```
(option xb assumed; fitted values)
. list q10bmihat q90bmihat in -1
```

	q10bmi~t	q90bmi~t
771.	20.73985	30.82972

(20.73985, 30.82972). Unconditional: (20.2, 30.95)

Question 6

(a)

```
. use "voucher.dta", clear
. count if select == 0
468
. count if selectyrs == 4
108
. count if choiceyrs == 4
56
```

468 students were never awarded a voucher. 108 had a voucher available for four years. 56 attended a choice school for four years.

(b)

```
. regr choiceyrs selectyrs, r
Linear regression
```

```
Number of obs    =      990
F(1, 988)        =    1665.27
Prob > F         =      0.0000
R-squared        =      0.7898
Root MSE        =      .576
```

	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
choiceyrs						
selectyrs	.7668317	.0187913	40.81	0.000	.7299562	.8037073
_cons	.0199189	.0105037	1.90	0.058	-.0006931	.040531

They are highly positively related, as expected. The p-value is 0.000 and the relationship is very strong. *selectyrs* is a sensible IV candidate for *choiceyrs* as it is highly correlated with *selectyrs* and not correlated with u_1 because it was randomly selected.

(c)

```
. regr mnce choiceyrs, r
Linear regression
```

```
Number of obs    =      990
F(1, 988)        =     13.58
Prob > F         =      0.0002
R-squared        =      0.0122
Root MSE        =     20.754
```

	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
mnce						
choiceyrs	-1.837014	.4985704	-3.68	0.000	-2.815393	-.858636
_cons	46.2344	.8973782	51.52	0.000	44.47342	47.99539

```
. regr mnce choiceyrs black hispanic female, r
Linear regression
```

```
Number of obs    =      990
F(4, 985)        =      20.28
Prob > F         =      0.0000
R-squared        =      0.0868
Root MSE        =     19.986
```

	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
mnce						
choiceyrs	-.5652475	.4940605	-1.14	0.253	-1.53478	.4042845
black	-16.01743	1.926572	-8.31	0.000	-19.79808	-12.23677
hispanic	-13.40287	2.41094	-5.56	0.000	-18.13404	-8.671704
female	1.352745	1.279764	1.06	0.291	-1.158633	3.864123
_cons	57.12192	1.879984	30.38	0.000	53.43268	60.81115

The slope estimator of *choiceyrs* is -1.837014. It does not makes sense as the more a student attends a choice school, the less they do well on the math exam. It becomes -.5652475 when I add *black*, *hispanic*, and *female*, making it less negatively related.

(d) *choiceyrs* might be endogenous in this equation because student have to apply for the voucher in order to be considered awarded, which is not a random process even though the vouchers were chosen by lottery among those who applied.

(e)

```
. ivregress 2sls mnce (choiceyrs = selectyrs) black hispanic female, r
```


Instrumental variables 2SLS regression Number of obs = 990
 Wald chi2(4) = 80.28
 Prob > chi2 = 0.0000
 R-squared = 0.0864
 Root MSE = 19.939

mnce	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
choiceyrs	-.2413189	.5917809	-0.41	0.683	-1.401188	.9185504
black	-16.31692	1.947611	-8.38	0.000	-20.13417	-12.49967
hispanic	-13.7754	2.41278	-5.71	0.000	-18.50436	-9.04644
female	1.319709	1.277918	1.03	0.302	-1.184964	3.824383
_cons	57.06804	1.87722	30.40	0.000	53.38875	60.74732

Instrumented: choiceyrs
Instruments: black hispanic female selectyrs

Using IV does not produce a positive effect of attending a choice school as the coefficient of *choiceyrs* is -.2413189, which is still negative. However, the coefficient did increase from -.5652475. As the other explanatory variables are not correlated with the instrument variable *selectyrs* and therefore their coefficients do not differ from the OLS ones.

(f)

```
. regr mnce choiceyrs black hispanic female mnce90, r
```


Linear regression Number of obs = 328
 F(5, 322) = 49.77
 Prob > F = 0.0000
 R-squared = 0.4237
 Root MSE = 16.029

mnce	Coefficient	Robust std. err.	t	P> t	[95% conf. interval]	
choiceyrs	.4105823	.7544828	0.54	0.587	-1.073756	1.894921
black	-8.305183	2.552212	-3.25	0.001	-13.3263	-3.284067
hispanic	-4.10498	3.465353	-1.18	0.237	-10.92257	2.712612
female	-.882847	1.784385	-0.49	0.621	-4.393373	2.627679
mnce90	.6203655	.0473119	13.11	0.000	.5272861	.7134449
_cons	22.1529	3.599737	6.15	0.000	15.07092	29.23487

```
. ivregress 2sls mnce (choiceyrs = selectyrs) black hispanic female mnce90, r
```


Instrumental variables 2SLS regression Number of obs = 328
 Wald chi2(5) = 258.25
 Prob > chi2 = 0.0000
 R-squared = 0.4173
 Root MSE = 15.969

mnce	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
choiceyrs	1.799385	.9378768	1.92	0.055	-.0388202	3.637589
black	-9.067109	2.556081	-3.55	0.000	-14.07694	-4.057283
hispanic	-5.00373	3.43925	-1.45	0.146	-11.74453	1.737076
female	-1.020484	1.773235	-0.58	0.565	-4.495961	2.454992
mnce90	.6288128	.0468642	13.42	0.000	.5369606	.7206649
_cons	21.53886	3.585963	6.01	0.000	14.5105	28.56722

Instrumented: choiceyrs
Instruments: black hispanic female mnce90 selectyrs

β_1 in OLS is .4105823 and β_1 in IV is 1.799385. For the IV estimate, each year in a choice school is worth 1.80 on the math percentile score. Not even 2 percentile change can't be seen as a practically large effect.

(g) Compared to part (d) where there are 990 observations, there are only 328 observations for the analysis from part (f). This makes the analysis from part (f) not entirely convincing.

(h)

```
. ivregress 2sls mnce (choiceyrs1 choiceyrs2 choiceyrs3 choiceyrs4 = /*
```


> */ selectyrs1 selectyrs2 selectyrs3 selectyrs4) black hispanic female, r
Instrumental variables 2SLS regression Number of obs = 990

Wald chi2(7) = 83.85
 Prob > chi2 = 0.0000
 R-squared = 0.0850
 Root MSE = 19.955

mnce	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
choicelyrs1	.3899757	2.461086	0.16	0.874	-4.433664	5.213616
choicelyrs2	.7736516	3.919113	0.20	0.844	-6.907669	8.454972
choicelyrs3	-4.284797	3.559596	-1.20	0.229	-11.26148	2.691882
choicelyrs4	2.407061	4.071456	0.59	0.554	-5.572846	10.38697
black	-16.29717	2.016116	-8.08	0.000	-20.24869	-12.34566
hispanic	-13.36599	2.568347	-5.20	0.000	-18.39985	-8.332119
female	1.36639	1.279023	1.07	0.285	-1.140448	3.873228
_cons	56.88582	1.895133	30.02	0.000	53.17143	60.60021

Instrumented: choicelyrs1 choicelyrs2 choicelyrs3 choicelyrs4
 Instruments: black hispanic female selectyrs1 selectyrs2 selectyrs3
 selectyrs4

(i) . ivregress 2sls mnce (choicelyrs = /*
 > */ selectyrs1 selectyrs2 selectyrs3 selectyrs4) black hispanic female, r
 Instrumental variables 2SLS regression

Number of obs = 990
 Wald chi2(4) = 80.28
 Prob > chi2 = 0.0000
 R-squared = 0.0865
 Root MSE = 19.939

mnce	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
choicelyrs	-.252745	.5906766	-0.43	0.669	-1.41045	.9049599
black	-16.30635	1.946441	-8.38	0.000	-20.12131	-12.4914
hispanic	-13.76226	2.4129	-5.70	0.000	-18.49146	-9.033064
female	1.320875	1.278125	1.03	0.301	-1.184203	3.825953
_cons	57.06994	1.876938	30.41	0.000	53.39121	60.74867

Instrumented: choicelyrs
 Instruments: black hispanic female selectyrs1 selectyrs2 selectyrs3
 selectyrs4

Here, β_1 estimate is -.252745 whereas it was -.2413189 in part (e). They are very similar to each other.

. ivregress gmm mnce (choicelyrs = /*
 > */ selectyrs1 selectyrs2 selectyrs3 selectyrs4) black hispanic female, r
 Instrumental variables GMM regression

Number of obs = 990
 Wald chi2(4) = 82.53
 Prob > chi2 = 0.0000
 R-squared = 0.0864
 Root MSE = 19.939

GMM weight matrix: Robust

mnce	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
choicelyrs	-.2437544	.5907315	-0.41	0.680	-1.401567	.9140581
black	-16.46039	1.938796	-8.49	0.000	-20.26036	-12.66042
hispanic	-13.83923	2.409442	-5.74	0.000	-18.56164	-9.116806
female	1.34696	1.275053	1.06	0.291	-1.152097	3.846017
_cons	57.17299	1.873959	30.51	0.000	53.50009	60.84588

Instrumented: choicelyrs
 Instruments: black hispanic female selectyrs1 selectyrs2 selectyrs3
 selectyrs4

. estat overid
 Test of overidentifying restriction:
 Hansen's J chi2(3) = 1.71092 (p = 0.6345)

The p-value for the overidentification test is 0.6345.

(j) We could include *selectyrs* as a covariate. This would enable us to see the effect of each of other covariates holding *selectyrs* constant.