School of Economics

Faculty of Arts and Social Sciences

Group Assessment Cover Sheet

(To be completed by students, dated and attached to front of assessment)

Assessment title: Applied project

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Unit of Study code & name: ECMT6002 Econometric Applications

Lecturer/Tutor's name: Dr Jian Hong Lecture/Tutorial day/time: 5-Aug-2019 18:00

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Levitt (1997) reveals the causal effect of police on crime by using the timing of mayoral and gubernatorial election years as an instrumental variable. Based on those previous researches, the existence of police budget cycles mentioned in the paper could be applied to public policies for solving the problem of the joint determination of crime and police staffing and provide more reliable estimates.

Fisher and Nagin (1978) state that the endogeneity of police on crime rates leads to the bias of the estimates in Cameron's (1988) research. The result is similar to the previous study of Levitt in 1996 and inspires Levitt to apply a different approach to break the simultaneity between police and crime.
Bekker (1994) illustrates that 2SLS is biased towards the OLS estimate and motivate Levitt (1997) to adapt the LIML approach which is more sensitive to other misspecification with lower asymptotic standard errors in estimating the effect of police on crime by IV.

Three types of crime: murder, rape and larceny are assigned for our group. The summary statistics for the variables are presented in Table 1.

Table 1 Summary statistics

			Std. Dev.			
Variable		Mean	Within-city	Across cities	Min	Max
P		2002.891	497.0974	3859.996	-327	31671
Crime		28493.42	9064.557	33781.18	1510	313787
	murder	155.0461	54.84969	259.8505	1	2245
	rape	456.7879	145.7493	542.3719	3	4054
	larceny	28394.4	9068.521	33289.49	1429	308479
rincpc		12.04567	1.145402	1.423304	7.425068	19.14193
unemp		0.065293	0.0181682	0.0091047	0.02	0.15458
citypop		718042.5	82085.36	1043302	85000	7896000
sta_edu		765.2299	79.13653	94.8541	445.9162	1193.437
sta_welf		255.1592	62.07046	110.5749	33.49282	847.7429
price		0.81	0.2998705	6.31E-09	0.388	1.307

After browsing the given data, there are three issues with the data. Initially, the minimum of sworn police is negative which does not make sense; therefore, this incorrect data should be dropped. Secondly, there are missing values in some observations, and they are dropped by Stata in estimation. Thirdly, there are some unreasonable values, which quietly deviate from the previous values. For example, the previous values of P are among 300 and 1000 and then following by an extreme value of 80300. Considering the reliability of the data, these invalid observations should be dropped.

Figure 1 presents the data points of (Cit; Pit). It demonstrates that there is a positive relationship between the number of sworn policers and reported crime, meaning that the reported crime increases with the police.

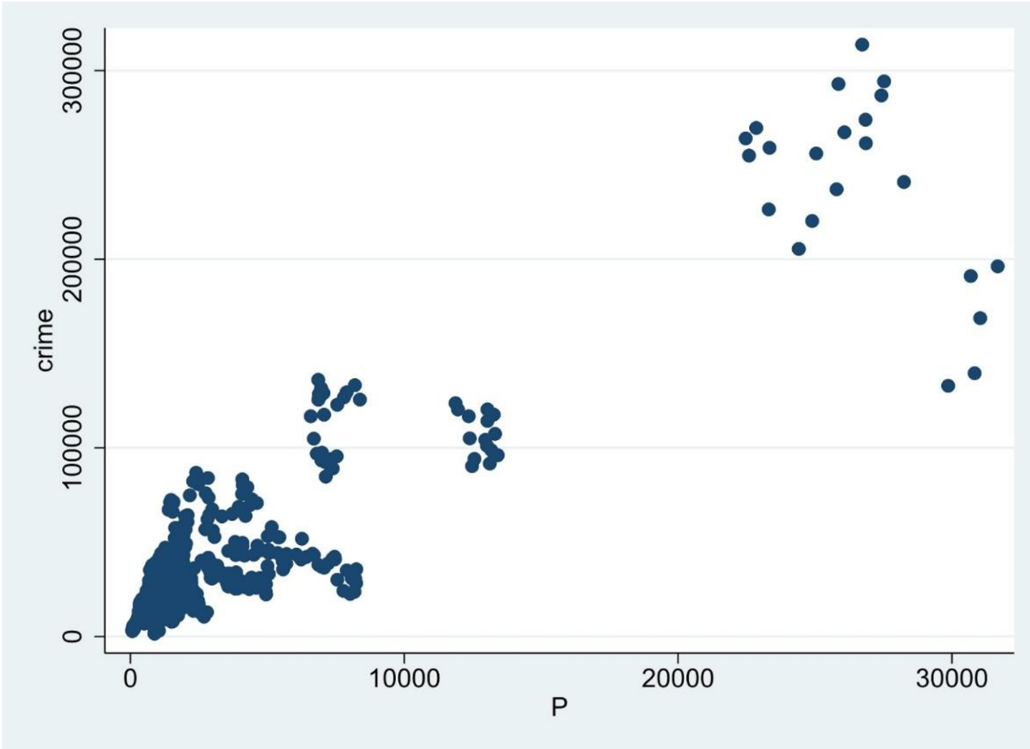

Figure 1 (Cit, Pit)

The research focuses on the causal effect of police on crime by using the election years as instruments. The coefficient β_1 in the model (1) is the elasticity of crime with respect to hiring sworn police, which measures the effect of the change in the policy rate on the reported crime rate, holding all other factors constant. β_2 is the elasticity of reported crime with respect to once-lagged sworn police. It is supposed to measure the tradeoff between the crime rate and the previous police rate, controlling for the other factors. Levitt (1997) concludes that police can reduce crime, which means the sign of β's should be negative. However, figure 1 presents an adverse pattern that increasing police leads to higher crime, meaning the sign of β's should be positive.

It is essential to include ln(Pi;t-1) in the model (1). Excluding ln(Pi;t-1) will violate the strict exogenous assumption. This assumption requires that the error term in model (1) is not only uncorrelated with Pt but also all past and future outcomes on P, therefore, ln(Pi;t-1) should be included in the model to ensure the error is uncorrelated with past values of P.

In practice, the observational data is usually generated in an uncontrolled environment so that it is difficult to control related variables of no interest to change together with the variables of interest. Including other covariates (in X) can greatly improve the accuracy of estimating the effect of police on crime and may significantly affect the final estimation results. On the other hand, the error term in the model can be reduced by adding covariates to increase the power of the factor tests.

Table 2 Estimates of the effect of in sworn officer on crime rates

Variables	(1) OLS	(2) DID	(3) 2SLS
In sworn officers	0.116	0.226	0.618
	(0.123)	(0.0502)	(1.098)
In once-lagged sworn officers	-0.358	-0.0737	2.468
	(0.121)	(0.0460)	(2.499)
Real income per capita	0.0303	0.00673	-0.00606

	(0.00789)	(0.0151)	(0.0352)
State unemployment rates	2.567	1.251	0.382
	(0.490)	(0.374)	(1.081)
Educational spending per capita	0.000705	-0.0000262	-0.0000296
	(-0.0000785)	(-0.0000838)	(-0.000228)
Public welfares spending per capita	-0.00120	0.000113	0.000177
	(0.000105)	(0.000164)	(0.000374)
Consumer price index	0	0	-8.965
	(0)	(0)	(7.543)
Constant	-5.662	-0.0970	0.509
	(0.230)	(0.0177)	(0.419)
Observations	1,023	956	956
R-squared	0.438	0.433	None
Year indicators?	Yes	Yes	Yes
Data differenced?	No	Yes	Yes
Instrument:	None (logs)	None (differences)	Mayoral election and governor election
p-value:	<0.01	<0.01	<0.01

Notes: the dependent variables in column (1) – (3) is ln crime rate for murder, rape and larceny. Column (1) selects log-log but column (2) and (3) applied log-differences. Column (3) treats ln sworn officers and ln sworn officers in the previous year as the endogenous variables and using mayoral election year in city(M) and a governor election year in the state(G) as instrumental variables The level of observation is city-year The observations run from 1969-1992 for 59 large U.S. cities. The last row of the table shows the p-value of different restriction on the effect of police on the crime rate.

Table 2 indicates the estimates for crime rates (murder/rape/larceny per capita) by the OLS. Column (1) applied log-log to estimates the Model (1) in OLS. The positive sign of β_1 and the negative sign of β_2 reveal that hiring more police currently leads to higher crime rates while hiring more police previously could reduce crime rates. The result of β_1 is consistent with previous expectation, showing the positive tendency between police force size and crime rates while the result of β_2 is the opposite.

The unobservable city effects captured in λ may be correlated to the regressors in the model (1). This may cause multicollinearity. It is not a violation of no perfect collinearity assumption but will cause difficulty in precise estimation.

In table 2, Column (2) applied log-differences to estimates the Model (2) by OLS. The positive sign of β_1 is consistency with the previous expectation while the sign of β_2 is negative in contrast to the expected signs. These results in accord with the OLS estimates for the model (1) illustrates that enhancing police force is associated with higher crime rates in this year and connected with lower crime rates in the past year.

To test the joint significance of β_1 and β_2 in the model (2), the null and alternative hypotheses are H_0: β_1=0, β_2=0 H_1: H_0 is false, we use F test statistic $F = \frac{(R^2_{UR}-R^2_R)/q}{(1-R^2_{UR})/(n-k-1)} \sim F_{q,n-k-1}$

Decision Rule: Reject H0 in favor of H1 if F > c, where c =$F_{q,n-k-1,\alpha}$ is the critical value for the F distribution with $dF_{q,n-k-1}$at α = 1% significance level. In this case, q=2, (n-k-1) =929 and c = 4.61

Decision: Since F = 13.21>c and p-value is 0.00001 than we reject the null H0 in favor of H1 at the 1% significance level.
Conclusion: β_1 and β_2 are jointly significant in explaining the crime rate, holding other variables constant.

It is concerned that the regressors in the model (2) may still be endogenous. According to Levitt (1997), higher crime rates are likely to cause larger marginal productivity of police. Cities tend to enhance the police force to cope with the problem of crime rates growth since police reduce crime. Therefore, crime rates and police rates are jointly determined, which results in the problem of simultaneity and violates MLR.4.

Levitt (1997) proposed to use the timing of mayoral and gubernatorial elections (Mit; Git) as an instrument for police hiring. To be valid instruments, three conditions should be held. Firstly, Git and Mit should be exogenous, i.e cov(Git;Mit,u)=0. Secondly, they should be correlated with the endogenous variables. Estimating by Stata, table 3 demonstrates among the endogenous regressors and proposed instruments. Thirdly, G and M should be excluded from the regression model.

Table 3 correlation among D.logP LD.logP G M

```
. correlate D.logP D.L.logP G M
(obs=1,214)
```

	D. logP	LD. logP	G	M
logP				
D1.	1.0000			
LD.	-0.0833	1.0000		
G	0.0673	0.0091	1.0000	
M	0.0308	0.0197	-0.2247	1.0000

For more precise estimation, we apply 2SLS for the model (2). The 2SLS estimation procedure consists of two stages.
Stage 1: generate a constructed instrument variable ^Pit by regressing ^Pit on other exogenous variables (D.Xit, G, M). Similarly, regress Pit-1 on other exogenous variables to generate a new instrument ^Pit-1. Since ^Pit and ^Pit-1 are a function of exogenous variables, they are exogenous.
Stage 2: regress ^Cit on (^Pit, ^Pit-1, D.Xit) to estimate (β_1, β_2).

To test the endogeneity, we perform the Wu-Hausman test.
The null and alternative hypothesis: $H_0: plim\left(\frac{1}{n}\sum D.lnP_{i,t}\ \ u_{i,t}\right) = 0$, $H_1: plim\left(\frac{1}{n}\sum D.lnP_{i,t}\ \ u_{i,t}\right) \neq 0$
WH test statistic: $WH = (\hat{}\beta_1^{OLS} - \hat{}\beta_1^{IV})^2/(Var(\hat{}\beta_1^{IV}) - Var(\hat{}\beta_1^{OLS}))$. Decision rule: reject the null hypothesisH_0 in favour of H_1 at level αif WH>x_a^2(1)
Decision: F=4.63127 and p = 0.01 then reject the null hypothesis $H_0: plim\left(\frac{1}{n}\sum D.lnP_{i,t}\ \ u_{i,t}\right) = 0$ in favor of $H_1: plim\left(\frac{1}{n}\sum D.lnP_{i,t}\ \ u_{i,t}\right) \neq 0$ at 1% level of significant.
Conclusion: The regressors in the model (2) are endogenous. The estimates from OLS and IV get closer and closer as n increase and M and G are effective IV.

Column (3) in Table 2 reports the elasticity of crime with respect of in sworn police by 2SLS based on the effective instrument variables such as mayoral election and governor election to solve the problem of endogeneity. β_1 shows that there is a positive correlation between reported crime rate and the policy rate while the stronger positive connection between reported crime rate and lagged in sworn policy rate is reflected by β_2, holding other factors constant. Hiring more police still could not decline the crime rate in contrast to the conclusion of literature about the negative relationship between the police force and crime rate.

Because property crime (larceny) occupied the largest proportion within assigned crime(Murder/Rape/larceny) by $\frac{larceny}{assigned\ \ crime} \times 100\% = \frac{232069}{232069+3507+1622} = 97.8\%$ in our paper, the number of property crime may denote the results, similarly, Levitt (1997) also reports that Larceny crime rate per capita alone is positively correlated with the changes in sworn police.

Based on our estimation result, there is an ambiguous causal effect of the crime on the police, which is entirely different from Levitt's (1997) conclusion that police reduce both kinds of crime and have a more substantial effect on violent crime than on property crime.

McCrary (2002) points out that a weighting error in Levitt's estimating process caused incorrect estimates and mistaken inferences. Levitt's estimation program gave more weight to crimes with higher variability, violating the original intention of the weighting procedure, and led to biased standard errors. After McCrary's replication with the correct weight, the results differ from Levitt's main conclusion, and the recalculated 2SLS estimates fail to show the causal effect of police on any crime categories.

Another issue with Levitt's paper is the weak instruments of using electoral years. Although Levitt (1997) provides convincing evidence of the relationship between elections and police hiring, through the precise recalculation of McCrary (2002), it appears impossible to uncover the causal effect of police on crime by using electoral cycles. Elections do significantly predict growth rates of sworn policers, but they are not useful to predict crime growth. Levitt (2002) states four approaches to precisely estimate the effect of police on crime (using elections as an instrument, firefighters as instruments, Granger causality, and high-frequency time-series variation), which similarly fails to uncover the causal effect that police reduce crime.

Appendix-Code

Q3

```
xtset city year
gen crime=murder+rape+larceny
sum murder rape larceny P year citypop rincpc unemp sta_educ sta_welf price
xtsum murder rape larceny P rincpc unemp sta_educ sta_welf price
graph twoway (scatter crime P), title("scatterplot(crime P)")
```

Q5

```
gen crimerate=(murder+rape+larceny)/citypop
gen policerate=P/citypop
drop if P<0
drop if P>80000
gen logP=log(policerate)
gen logc=log(crimerate)
reg logc logP L.logP i.year rincpc unemp sta_educ sta_welf price, robust
```

```
. reg logc logP L.logP i.year rincpc unemp sta_educ sta_welf price, robust
note: price omitted because of collinearity

Linear regression                               Number of obs     =      1,023
                                                F(25, 997)        =      26.32
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4384
                                                Root MSE          =     .25628
```

logc	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
logP						
--.	.1157731	.1232675	0.94	0.348	-.1261204	.3576667
L1.	-.358271	.1205832	-2.97	0.003	-.5948971	-.121645
year						
72	-.0750758	.0626089	-1.20	0.231	-.1979362	.0477847
73	-.0558645	.0602216	-0.93	0.354	-.1740401	.0623112
74	.1040223	.0564276	1.84	0.066	-.0067082	.2147527
75	.1673287	.0570678	2.93	0.003	.0553419	.2793156
76	.2285806	.0563255	4.06	0.000	.1180504	.3391108
77	.1565789	.0552148	2.84	0.005	.0482283	.2649295
78	.1672764	.0570599	2.93	0.003	.0553052	.2792476
79	.2533614	.0584156	4.34	0.000	.1387298	.3679929
80	.3441192	.0590945	5.82	0.000	.2281554	.4600831
81	.3697394	.0595164	6.21	0.000	.2529475	.4865312
82	.3182267	.0609634	5.22	0.000	.1985955	.437858
83	.2384742	.0623907	3.82	0.000	.1160421	.3609062
84	.2710334	.0586137	4.62	0.000	.1560131	.3860537
85	.301874	.0605619	4.98	0.000	.1830306	.4207173
86	.3082078	.0620875	4.96	0.000	.1863705	.430045
87	.3552107	.0628327	5.65	0.000	.2319112	.4785103
88	.3642397	.0651418	5.59	0.000	.2364089	.4920704
89	.3718741	.0648001	5.74	0.000	.2447139	.4990343
90	.3609311	.0635351	5.68	0.000	.2362533	.4856089
rincpc	.0303474	.007889	3.85	0.000	.0148664	.0458284
unemp	2.567318	.4902302	5.24	0.000	1.605316	3.529319
sta_educ	.0007051	.0000785	8.98	0.000	.0005511	.000859
sta_welf	-.0012025	.0001048	-11.48	0.000	-.0014082	-.0009969
price	0	(omitted)				
_cons	-5.661515	.2295152	-24.67	0.000	-6.111904	-5.211127

Q7

```
reg D.logc D.logP LD.logP i.year D.rincpc D.unemp D.sta_educ D.sta_welf D.price, robust
```

```
. regress D.logc D.logP LD.logP i.year D.rincpc D.unemp D.sta_educ D.sta_welf D.price
> , robust
note: D.price omitted because of collinearity

Linear regression                               Number of obs     =        956
                                                F(24, 931)        =      28.56
                                                Prob > F          =     0.0000
                                                R-squared         =     0.4330
                                                Root MSE          =     .08264
```

D.logc	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
logP						
D1.	.2262012	.0501668	4.51	0.000	.1277481	.3246543
LD.	-.0736966	.0459772	-1.60	0.109	-.1639276	.0165343
year						
73	.1035408	.0208417	4.97	0.000	.0626387	.1444428
74	.2559511	.0225526	11.35	0.000	.2116913	.3002109
75	.2191481	.0242179	9.05	0.000	.1716202	.2666761
76	.164153	.0203573	8.06	0.000	.1242015	.2041045
77	.0038853	.0194886	0.20	0.842	-.0343613	.0421318
78	.1041449	.0195505	5.33	0.000	.0657768	.1425131
79	.1713744	.022608	7.58	0.000	.1270059	.2157429
80	.1889939	.0245939	7.68	0.000	.140728	.2372598
81	.1009205	.0197751	5.10	0.000	.0621115	.1397295
82	.0718719	.0225365	3.19	0.001	.0276436	.1161002
83	.030234	.0196229	1.54	0.124	-.0082762	.0687442
84	.1144782	.0204816	5.59	0.000	.0742827	.1546738
85	.1483386	.0192498	7.71	0.000	.1105606	.1861167
86	.1320443	.0181204	7.29	0.000	.0964828	.1676058
87	.1316679	.0200663	6.56	0.000	.0922874	.1710484
88	.121164	.0197102	6.15	0.000	.0824823	.1598456
89	.1061594	.0215406	4.93	0.000	.0638856	.1484331
90	.0781896	.0201571	3.88	0.000	.0386309	.1177483
rincpc						
D1.	.0067275	.0151097	0.45	0.656	-.0229256	.0363806
unemp						
D1.	1.251218	.3735116	3.35	0.001	.5181962	1.984241
sta_educ						
D1.	-.0000262	.0000838	-0.31	0.755	-.0001906	.0001383
sta_welf						
D1.	.0001134	.000164	0.69	0.489	-.0002084	.0004353
price						
D1.	0	(omitted)				
_cons	-.0970321	.0176988	-5.48	0.000	-.1317663	-.0622979

Q8
test D.logP D.L.logP

```
. test D.logP D.L.logP

 ( 1)  D.logP = 0
 ( 2)  LD.logP = 0

       F(  2,   931) =   13.21
            Prob > F =    0.0000
```

Q10.
correlate D.logP D.L.logP G M

```
. correlate D.logP D.L.logP G M
(obs=1,214)

             |       D.      LD.
             |     logP     logP        G        M
-------------+------------------------------------
        logP |
         D1. |   1.0000
         LD. |  -0.0833   1.0000
           G |   0.0673   0.0091   1.0000
           M |   0.0308   0.0197  -0.2247   1.0000
```

Q11
ivregress 2sls D.logc D.rincpc D.unemp D.sta_educ D.sta_welf D.price i.year (D.L.logP D.logP =M G), robust

```
. ivregress 2sls D.logc D.rincpc D.unemp D.sta_educ D.sta_welf D.price i.year  (D.L.l
> ogP  D.logP =M G), robust
note: 69.year identifies no observations in the sample
note: 70.year identifies no observations in the sample
note: 71.year identifies no observations in the sample
note: 89.year omitted because of collinearity
note: 90.year omitted because of collinearity
note: 91.year identifies no observations in the sample
note: 92.year identifies no observations in the sample

Instrumental variables (2SLS) regression          Number of obs   =        956
                                                  Wald chi2(24)   =     170.32
                                                  Prob > chi2     =     0.0000
                                                  R-squared       =          .
                                                  Root MSE        =     .17319

------------------------------------------------------------------------------
             |               Robust
      D.logc |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        logP |
         LD. |   2.467734   2.498951     0.99   0.323    -2.430119    7.365588
         D1. |   .6183177   1.098491     0.56   0.574    -1.534684     2.77132
             |
      rincpc |
         D1. |  -.0060589    .035197    -0.17   0.863    -.0750438     .062926
             |
       unemp |
         D1. |   .3822612    1.08135     0.35   0.724    -1.737145    2.501668
             |
    sta_educ |
         D1. |  -.0000296   .0002283    -0.13   0.897    -.0004771    .0004178
             |
    sta_welf |
         D1. |   .0001767    .000374     0.47   0.637    -.0005564    .0009097
             |
       price |
         D1. |  -8.965411   7.542634    -1.19   0.235     -23.7487    5.817879
             |
        year |
         69  |          0  (empty)
         70  |          0  (empty)
         71  |          0  (empty)
         72  |  -.5980048   .4261286    -1.40   0.161    -1.433202     .237192
         73  |  -.3223511   .2855993    -1.13   0.259    -.8821155    .2374132
         74  |   .0172093   .1248437     0.14   0.890    -.2274799    .2618984
         75  |  -.0077994   .1073327    -0.07   0.942    -.2181676    .2025687
         76  |  -.1717935   .1934729    -0.89   0.375    -.5509933    .2074064
         77  |   -.265378   .1443133    -1.84   0.066    -.5482268    .0174709
         78  |   -.097891   .0858166    -1.14   0.254    -.2660885    .0703064
         79  |   .2601037   .1825192     1.43   0.154    -.0976274    .6178349
         80  |   .4891878   .3500802     1.40   0.162    -.1969568    1.175332
         81  |   .2647764   .2422246     1.09   0.274    -.2099751    .7395279
         82  |   .0171926   .0768047     0.22   0.823    -.1333419    .1677271
         83  |  -.3050705   .1884521    -1.62   0.105    -.6744299    .0642889
         84  |  -.0898555   .0895422    -1.00   0.316     -.265355     .085644
         85  |  -.1260619    .154539    -0.82   0.415    -.4289528     .176829
         86  |  -.3596884   .3303725    -1.09   0.276    -1.007207    .2878299
         87  |  -.1624498   .1589868    -1.02   0.307    -.4740582    .1491585
         88  |  -.0577812   .0725975    -0.80   0.426    -.2000696    .0845072
         89  |          0  (omitted)
         90  |          0  (omitted)
         91  |          0  (empty)
         92  |          0  (empty)
             |
       _cons |   .5092647   .4185924     1.22   0.224    -.3111613    1.329691
------------------------------------------------------------------------------
Instrumented:  LD.logP D.logP
Instruments:   D.rincpc D.unemp D.sta_educ D.sta_welf D.price 72.year
               73.year 74.year 75.year 76.year 77.year 78.year 79.year
               80.year 81.year 82.year 83.year 84.year 85.year 86.year
               87.year 88.year M G
```

Q12
estat endogenous

```
. estat endogenous

  Tests of endogeneity
  Ho: variables are exogenous

  Robust score chi2(2)            =  8.78401  (p = 0.0124)
  Robust regression F(2,929)      =  4.63127  (p = 0.0100)
```

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