Problem Set 3: Instrumental Variables Key

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Empirical Analysis using Data from Ananat (2011, AEJ:AE)

This exercise uses data from Elizabeth Ananat's paper, "The Wrong Side(s) of the Tracks: The Causal Effects of Racial Segregation on Urban Poverty and Inequality," published in the *American Economic Journal: Applied Economics* in 2011. This paper studies how segregation has affected population characteristics and income disparity in US cities using the layout of railroad tracks as an instrumental variable.

Finding the data

I have downloaded Ananat's `aej_maindata.dta` file and made it available in the RCloud assignment workspace. I downloaded this data from the AER's website which links you to the ICPSR's data repository. Anyone can sign in to get access to the replication data files. These include the typical files in a replication folder: several datasets, several .do files (which is a STATA command file), and text files with the data descriptions which tell you about the different variables included in the dataset.

1 Set up and opening the data

1.1 Question: Load the have, dplyr, stargazer, lfe and ggplot2 packages and the data contained in the `aej_maindata.dta` file. Make sure it is stored as a data frame.

Code:

```
library(haven)
library(dplyr)
```

```
## Warning: package 'dplyr' was built under R version 4.1.2
```

```
##
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
##
##     filter, lag
```

```
## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```
library(stargazer)
```

```
##
## Please cite as:
```

```
##  Hlavac, Marek (2018). stargazer: Well-Formatted Regression and Summary Statistics Tables.
```

```
##  R package version 5.2.2. https://CRAN.R-project.org/package=stargazer
```

```
library(lfe)
```

```
## Loading required package: Matrix
```

```
library(ggplot2)

mydata<-read_dta("aej_maindata.dta")
mydata<-as.data.frame(mydata)
```

1.2 Question:The dataset contains many variables, some of which are not used in this exercise. Keep the following variables in the final dataset (Hint: use the `select` function in `dplyr`).

Name	Description
dism1990	1990 dissimilarity index
herf	RDI (Railroad division index)
lenper	Track length per square km
povrate_w	White poverty rate 1990
povrate_b	Black poverty rate 1990
area1910	Physical area in 1910 (1000 sq. miles)
count1910	Population in 1910 (1000s)
ethseg10	Ethnic Dissimilariy index in 1910
ethiso10	Ethnic isolation index in 1910
black1910	Percent Black in 1910
passpc	Street cars per capita 1915
black1920	Percent Black 1920
lfp1920	Labor Force Participation 1920
incseg	Income segregation 1990
pctbk1990	Percent Black 1990
manshr	Share employed in manufacturing 1990
pop1990	Population in 1990

You can find the detailed description of each variable in the original paper.

Code:

```
mydata2<-mydata[, c("dism1990", "herf", "lenper", "povrate_w", "povrate_b", "area1910",
                    "count1910","ethseg10","ethiso10","black1910","passpc","black1920",
                    "lfp1920","incseg", "pctbk1990","manshr","pop1990" )]
```

2 Data description:

2.1 Question: How many observations are contained in the data. What is the level of an observation?

Answer:

```
nrow(mydata)
```

[1] 121

The data contains 121 observations where each observations is for one city/town.

2.2 Question: Report summary statistics of the following variables in the dataset:"dism1990", "herf", "lenper", "povrate_w", "povrate_b". Present these summary statistics in a formatted table, you can use `stargazer` or other packages.

Code:

```
stargazer(mydata2[,c("dism1990", "herf", "lenper", "povrate_w", "povrate_b")], type = "latex")
```

% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
% Date and time: Thu, Mar 16, 2023 - 10:19:48 AM

Table 2:

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
dism1990	121	0.569	0.135	0.329	0.457	0.673	0.873
herf	121	0.723	0.141	0.238	0.638	0.830	0.987
lenper	121	0.001	0.001	0.0002	0.0004	0.001	0.013
povrate_w	121	0.095	0.035	0.035	0.069	0.114	0.216
povrate_b	121	0.264	0.080	0.093	0.209	0.313	0.504

3 Reduced Form:

3.1 Question: We are interested in understanding how segregation affects population characteristics and income disparity in US cities. We will focus on two outcome variables: the poverty rate for blacks and whites. Regress these two outcome variables on segregation in 1990, our explanatory variable, and interpret your results. Report robust standard errors.

Hint 1: These exact results are reported in the second row of columns 1 and 2 of table 2.

Hint 2: Since the units of the explanatory variable are strange, it is helpful to interpret the effect in terms of standard deviations. So instead of interpreting a one unit change in `dism1990`, interpret a one standard deviation (0.14) change in `dism1990`.

Code:

```
reg1<-felm(povrate_w~dism1990, mydata2)
reg2<-felm(povrate_b~dism1990, mydata2)

stargazer(reg1,reg2, type ="latex",se = list(reg1$rse, reg2$rse))
```

% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
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Table 3:

	Dependent variable:	
	povrate_w	povrate_b
	(1)	(2)
dism1990	-0.073^{***}	0.182^{***}
	(0.019)	(0.045)
Constant	0.136^{***}	0.161^{***}
	(0.012)	(0.029)
Observations	121	121
R^2	0.081	0.095
Adjusted R^2	0.074	0.088
Residual Std. Error (df = 119)	0.033	0.076
Note:	*p<0.1; **p<0.05; ***p<0.01	

Answer: For the explanatory variable, one standard deviation is about 0.14 as reported in the summary statistics. It is helpful for interpretation to interpret these effects in terms of standard deviations of the explanatory variable. Thus, we can see that a one standard deviation increase in the segregation index is associated with a $(0.14 * (-0.073) = -0.0102)$, one percentage point decrease in white poverty and a $(0.14 * (0.182) = 0.025)$, 2.5 percentage point increase in black poverty.

3.2 Question: Explain the problem with giving a causal interpretation to the estimates you just produced. Give examples of specific factors that might make a causal interpretation of your result problematic.

Answer: There are many problems with giving these estimates a causal interpretation. Omitted Variable Bias is a particular concern. There are many variables that are jointly correlated with both segregation and poverty, such as political corruption or the presence of industrial sectors that are associated with occupational segregation to name just a few. Omission of any of these variables from our regression could lead to biased causal estimates. In addition, there is also the concern of selection as segregation may induce selective migration. Finally, reverse causality could also be a concern as cities with greater black poverty could elect to implement more segregating policies.

4 Validity of the instrument:

4.1 Question: Estimate the following regression and interpret it's coefficients,

$$dism1990_i = \beta_0 + \beta_1 RDI_i + \beta_2 tracklength_i + \epsilon.$$

Hint 1: These exact results are reported in the first column of the top panel of table 1.

Hint 2: Since the units of the explanatory variable are strange, it is helpful to interpret the effect in terms of standard deviations. So instead of interpreting a one unit change in `herf`, interpret a one standard deviation (0.14) change in `herf`.

Code:

```
regfirststage<-felm(dism1990~herf+lenper, mydata2)

stargazer(regfirststage, type = "latex",se = list(regfirststage$rse))
```

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Table 4:

	Dependent variable:
	dism1990
herf	0.357***
	(0.088)
lenper	18.514*
	(10.731)
Constant	0.294***
	(0.064)
Observations	121
R^2	0.203
Adjusted R^2	0.189
Residual Std. Error	0.122 (df = 118)
Note:	*p<0.1; **p<0.05; ***p<0.01

Answer: For the explanatory variable, one standard deviation is, here too, about 0.14 as reported in the summary statistics. It is helpful for interpretation to interpret these effects in terms of standard deviations of the explanatory variable. Thus, we can see that a one standard deviation increase in the RDI is associated with a $(0.14 * (0.357) = 0.049)$, a 5 point increase in the segregation index, which is about 0.37 standard deviations.

4.2 Question: In the context of instrumental variables, what is this regression referred to as and why is it important?

Answer: This regression is referred to as the first stage regression. It is a regression of the instrument on the endogenous explanatory variable. It is important since for the RDI to work as an instrument, it needs to have some explanatory power over the endogenous variable, segregation.

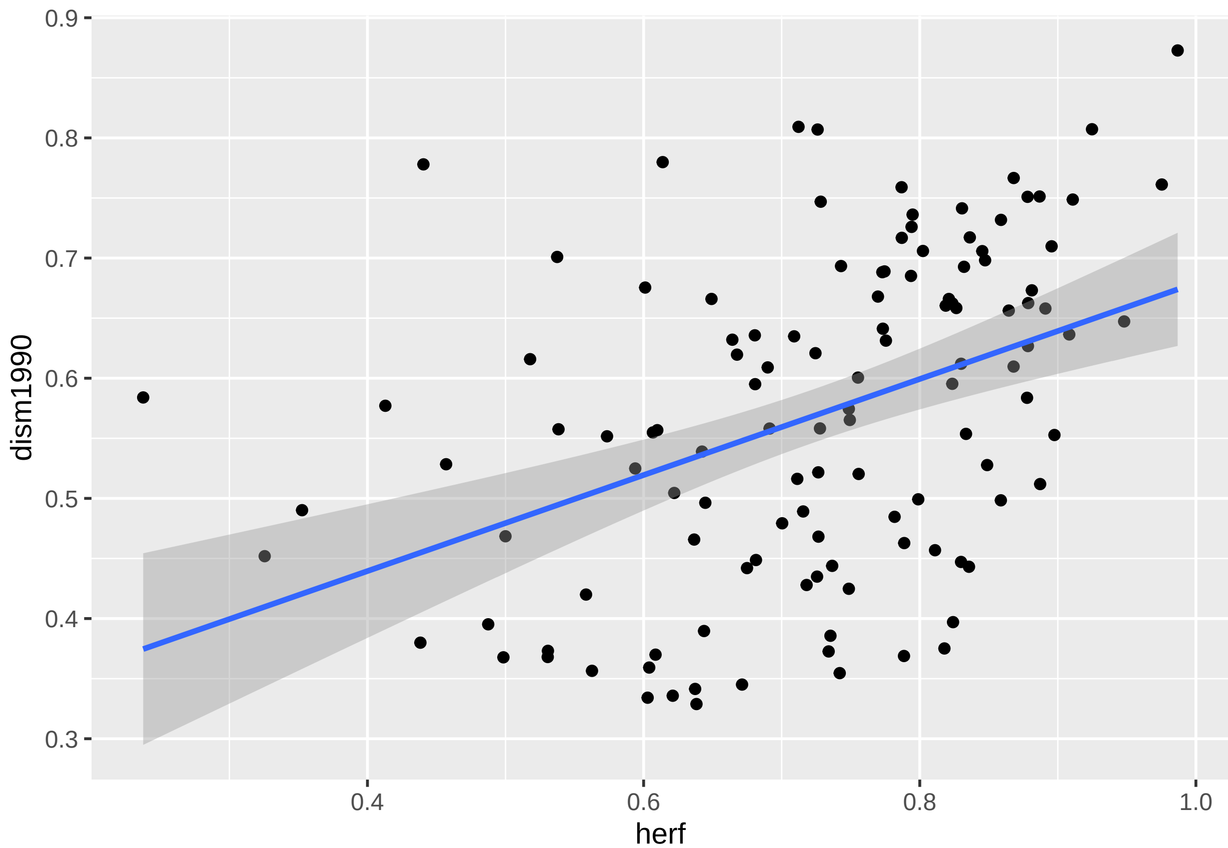
4.3 Question: Illustrate the relationship between the RDI and segregation graphically.

Hint: See figure 3.

Code:

```
myplot1<-ggplot(mydata, aes(x=herf, y=dism1990)) +
  geom_point()+
  geom_smooth(method='lm', aes(y = dism1990))
myplot1
```

```
## `geom_smooth()` using formula 'y ~ x'
```



4.4 Question: Is there a concern that this might be a weak instrument? Why would this be a problem?

Answer:

```
summary(regfirststage)$fstat
```

[1] 14.98272

The F-statistic for the first stage model is greater than 10, the benchmark used to detect weak instruments so the weak instrument problem likely does not apply here. Weak instruments are a problem because if the instrumental variable does not have good predictive power over the endogenous variable, any small bias that results from a violation of the exclusion restriction gets magnified to generate large bias.

4.5 Question: Regress the following cith characteristics on the RDI and track length: `area1910` `count1910`, `black1910`, `incseg`, `lfp1920`. Present your results and interpret your findings. Why do these results matter for answering our question of interest?

Hint: In stargazer, add the option `omit.stat=c( "ser")` to remove the residual standard errors from the table footer so that the table fits the width of a page.

Code and Answer:

```
regex1<-felm(area1910~herf+lenper, mydata2)
regex2<-felm(count1910~herf+lenper, mydata2)
regex3<-felm(black1910~herf+lenper, mydata2)
regex4<-felm(incseg~herf+lenper, mydata2)
regex5<-felm(lfp1920~herf+lenper, mydata2)


stargazer(regex1,regex2,regex3,regex4,regex5,
          type = "latex",
          se = list(regex1$rse,regex2$rse,regex3$rse,
                    regex4$rse,regex5$rse),
          omit.stat=c( "ser"))
```

% Table created by stargazer v.5.2.2 by Marek Hlavac, Harvard University. E-mail: hlavac at fas.harvard.edu
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Table 5:

	Dependent variable:				
	area1910	count1910	black1910	incseg	lfp1920
	(1)	(2)	(3)	(4)	(5)
herf	−3,992.637	665.751	−0.001	0.032	0.028
	(11,986.490)	(1,362.964)	(0.010)	(0.032)	(0.024)
lenper	−574,401.000	75,553.190	9.236***	−2.504	−3.427**
	(553,669.000)	(134,814.900)	(0.650)	(1.626)	(1.500)
Constant	18,409.570**	976.876	0.007	0.196***	0.401***
	(8,612.320)	(927.189)	(0.007)	(0.025)	(0.018)
Observations	58	121	121	69	121
R^2	0.007	0.006	0.290	0.028	0.015
Adjusted R^2	−0.029	−0.011	0.278	−0.001	−0.002
Note:					*p<0.1; **p<0.05; ***p<0.01

The RDI does not have a statistically significant effect on any of these city characteristics, holding the length of rail lines in the city constant. These regressions serve to support our assumption that the exclusion restriction holds. For our instrument to be valid, the only way that the RDI affects current poverty must be through it's effect on segregation. This is an assumption that cannot be tested directly. To determine whether or not we believe that it holds, we must evaluate the arguments presented by the author and evidence such as the results of these regressions. These regressions suggest that the RDI is not associated with city characteristics prior to the Great Migration and were not associated with different population characteristics at the beginning of the great migration, before segregation began to shape population characteristics.

4.6 Question: What are the two conditions necessary for a valid instrument? What evidence do you have that the RDI meet these conditions? Be specific in supporting this claim.

Answer: The two conditions are that we need a first stage and for the exclusion restriction to be satisfied:

1) $cov(z, x_i) \neq 0$
2) $cov(z, \nu) = 0$

We have seen above that there is a first stage and that the first stage is quite strong. Regarding the exclusion restriction, Ananat provides some evidence that it should hold through her discussion of the history of railroads and the regressions presented in table 1 though some concerns may still be valid.

4.7 Question: Do you believe the instrument is valid? Why/why not?

Answer: Being able to study how segregation impacts communities is an important and interesting question but finding a source of exogenous variation for segregation is not easy. The instrument proposed by Ananat may not be perfect but does provide plausibly exogenous variation with which to tackle this question. We have to be convinced that the way the railroads were laid out was not influenced by socio-economic characteristics that could explain patterns seen today and we also have to believe that the rail configuration is not correlated with who migrated to the city during the great migration in a way that she cannot detect. If, for instance, certain types of manufacturing plants are associated with black-white disparity were more likely to located in cities with certain types of rail configurations (due to topography for example) this could violate the exclusion restriction. While there are certainly stories that could be told that would challenge the validity of this instrument, it is a plausible source of exogenous variation in segregation, which is no small feat.

4.8 Question: Generate a table that estimates the effect of segregation on the poverty rate for blacks and whites by OLS and then using the RDI instrument. Make sure you report robust standard errors. How does the use of the RDI instrument change the estimated coefficients?

Hint: these will be the exact results reported in row 2 of columns 1-4 in table 2.

Code and Answer:

```
regmain1<-felm(povrate_w~dism1990, mydata2)
regmain2<-felm(povrate_b~dism1990, mydata2)
regmain3<-felm(povrate_w~lenper|0|(dism1990~herf+lenper), mydata2)
```

```
## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite
```

```
regmain4<-felm(povrate_b~lenper|0|(dism1990~herf+lenper), mydata2)
```

```
## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite
```

```
stargazer(regmain1,regmain2,regmain3,regmain4,
          type = "latex",
          se = list(regmain1$rse,regmain2$rse,regmain3$rse,regmain4$rse))
```

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Using the RDI instrument leads to much larger estimated effects then when using the simple OLS model. The effect of 1 unit on the segregation index on white poverty rate goes from -0.073 to -0.196 whereas the effect on black poverty rate goes from 0.182 to 0.258, a substantial change in both cases.

Table 6:

	Dependent variable:			
	povrate_w	povrate_b	povrate_w	povrate_b
	(1)	(2)	(3)	(4)
dism1990	-0.073^{***}	0.182^{***}		
	(0.019)	(0.045)		
lenper			0.602	-4.780
			(1.970)	(3.067)
‘dism1990(fit)‘			-0.196^{***}	0.258^{**}
			(0.065)	(0.108)
Constant	0.136^{***}	0.161^{***}	0.205^{***}	0.121^{**}
	(0.012)	(0.029)	(0.037)	(0.061)
Observations	121	121	121	121
R^2	0.081	0.095	-0.150	0.084
Adjusted R^2	0.074	0.088	-0.170	0.068
Residual Std. Error	0.033 (df = 119)	0.076 (df = 119)	0.037 (df = 118)	0.077 (df = 118)
Note:				*p<0.1; **p<0.05; ***p<0.01

4.9 Question: What is the reduced form equation?

Answer: The reduced form equation is the regression of the outcome variable directly on the instrument and any other exogenous variables. In this case it is

$$Y_i = \pi_0 + \pi_1 RDI_i + \pi_2 tracklength_i + \eta$$

4.10 Question: For the two poverty rates, estimate the reduced form on all the cities and illustrate the reduced form relationships graphically. (2 pages)

Code:

```
regrf1<-felm(povrate_w~herf+lenper, mydata2)
regrf2<-felm(povrate_b~herf+lenper, mydata2)

stargazer(regrf1,regrf2, type = "latex",se = list(regrf1$rse,regrf2$rse))
```

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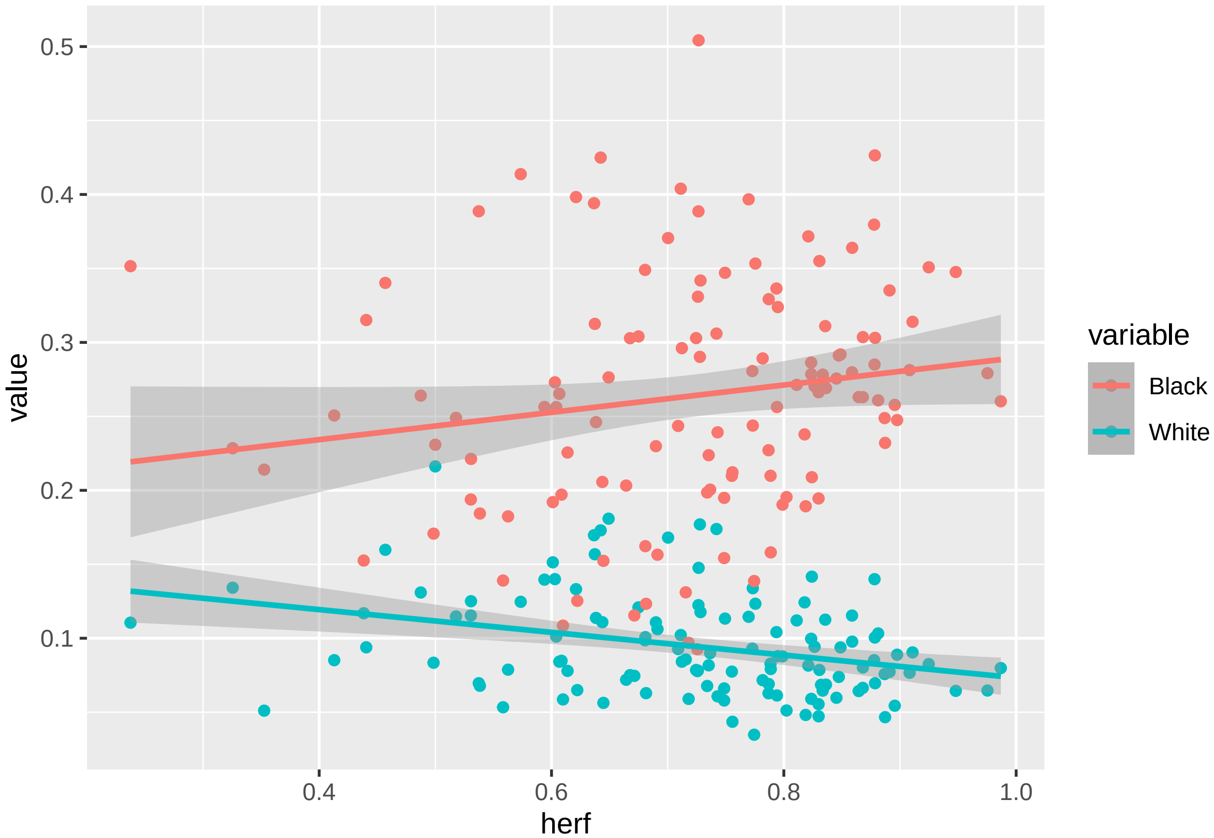
Table 7:

	Dependent variable:	
	povrate_w	povrate_b
	(1)	(2)
herf	-0.070^{***}	0.092^{*}
	(0.021)	(0.048)
lenper	-3.022^{***}	0.004
	(1.011)	(4.398)
Constant	0.148^{***}	0.197^{***}
	(0.017)	(0.036)
Observations	121	121
R^2	0.111	0.027
Adjusted R^2	0.096	0.010
Residual Std. Error (df = 118)	0.033	0.079
Note:	*p<0.1; **p<0.05; ***p<0.01	

```
plotted<-ggplot(mydata2, aes(herf, y = value, color = variable)) +
    geom_point(aes(y =povrate_w , col = "White")) +
    geom_point(aes(y = povrate_b, col = "Black"))+
    geom_smooth(method='lm', aes(y = povrate_w, col = "White"))+
    geom_smooth(method='lm', aes(y = povrate_b, col = "Black"))

plotted
```

```
## `geom_smooth()` using formula 'y ~ x'
## `geom_smooth()` using formula 'y ~ x'
```


0.5
0.4
0.3
0.2
0.1
value
0.4
0.6
0.8
1.0
herf
variable
Black
White

4.11 Question: Generate a table with six columns that check whether the main results are robust to adding additional controls for city characteristics. What do you conclude? (2 pages)

Hint: In stargazer, add the option `omit.stat=c( "ser")` to remove the residual standard errors from the table footer so that the table fits in a page.

Code:

```
regcont1<-felm(povrate_w~lenper+pctbk1990|0|(dism1990~herf+lenper+pctbk1990), mydata2)
```

```
## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite
```

```
regcont2<-felm(povrate_b~lenper+pctbk1990|0|(dism1990~herf+lenper+pctbk1990), mydata2)
```

```
## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite
```

```
regcont3<-felm(povrate_w~lenper+pctbk1990+manshr
               |0|(dism1990~herf+lenper+pctbk1990+manshr), mydata2)
```

```
## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite
```

```
regcont4<-felm(povrate_b~lenper+pctbk1990+manshr
               |0|(dism1990~herf+lenper+pctbk1990+manshr), mydata2)
```

```
## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite
```

```
regcont5<-felm(povrate_w~lenper+pctbk1990+manshr+pop1990
               |0|(dism1990~herf+lenper+pctbk1990+manshr+pop1990), mydata2)
```

```
## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite

## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite

## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite
```

```
regcont6<-felm(povrate_b~lenper+pctbk1990+manshr+pop1990
               |0|(dism1990~herf+lenper+pctbk1990+manshr+pop1990), mydata2)
```

```
## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite

## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
```

```
## rank-deficient or indefinite

## Warning in chol.default(mat, pivot = TRUE, tol = tol): the matrix is either
## rank-deficient or indefinite
```

```
stargazer(regcont1,regcont2,regcont3,regcont4,regcont5,regcont6,
          type = "latex",
          se = list(regcont1$rse,regcont2$rse,
                                   regcont3$rse,regcont4$rse,
                                   regcont5$rse,regcont6$rse),
          omit.stat=c( "ser"))
```

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Table 8:

	Dependent variable:					
	povrate_w	povrate_b	povrate_w	povrate_b	povrate_w	povrate_b
	(1)	(2)	(3)	(4)	(5)	(6)
lenper	−0.479	−2.331	1.214	−3.274	1.649	−4.070
	(1.801)	(2.402)	(3.586)	(4.590)	(3.661)	(4.826)
pctbk1990	0.211	−0.478*	0.254	−0.480*	0.233	−0.441
	(0.153)	(0.246)	(0.215)	(0.281)	(0.219)	(0.278)
manshr			0.135	−0.063	0.153	−0.096
			(0.158)	(0.239)	(0.166)	(0.246)
pop1990					0.000	−0.000*
					(0.000)	(0.000)
‘dism1990(fit)‘	−0.241**	0.360**	−0.338*	0.344	−0.354*	0.374
	(0.097)	(0.141)	(0.188)	(0.238)	(0.195)	(0.240)
Constant	0.219***	0.091	0.248***	0.116	0.252***	0.109
	(0.048)	(0.068)	(0.068)	(0.082)	(0.070)	(0.081)
Observations	121	121	111	111	111	111
R^2	−0.254	0.108	−0.535	0.086	−0.592	0.088
Adjusted R^2	−0.286	0.085	−0.593	0.052	−0.667	0.045
Note:						*p<0.1; **p<0.05; ***p<0.01

Answer: Controlling for additional city characteristics does not significantly alter the magnitude of the point estimates. If anything it makes the point estimates larger. This is evidence that confirms that the effect of RDI is operating through segregation and not via some other city characteristic.

5 Why Two Stage least squares?

Because the estimates in this paper only feature one endogenous regressor and one instrument, it is an excellent example with which to illustrate build intuition and see what the instrumental variables regressor is actually doing because in this scenario the IV estimator is exactly equal to the two stage least squares estimator ($\hat{\beta}_{IV} = \hat{\beta}_{2SLS}$).

5.1 Question: Estimate the first stage regression and use your estimates to generate the predicted values for the explanatory variable for all the observations.

Code:

```
regfs<-lm(dism1990~herf+lenper, mydata2)
mydata2$pred_dism1990<-predict(regfs)
```

5.2 Question: If our instrument is valid, the step above "removed" the "bad" endogenous variation from the predicted explanatory variable, keeping only the exogenous variation that is generated by the instrument. Now run the second stage by regressing our outcome variable on the predicted values generated above and the relevant controls. Compare your estimates from this regression to those generated earlier. How do they compare?

Code:

```
reg2sls1<-lm(povrate_w~pred_dism1990+lenper, mydata2)
reg2sls2<-lm(povrate_b~pred_dism1990+lenper, mydata2)

stargazer(reg2sls1,reg2sls2, type = "latex",se = list(reg2sls1$rse,reg2sls2$rse))
```

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% Date and time: Thu, Mar 16, 2023 - 10:19:51 AM

Table 9:

	Dependent variable:	
	povrate_w	povrate_b
	(1)	(2)
pred_dism1990	−0.196***	0.258*
	(0.061)	(0.148)
lenper	0.602	−4.780
	(2.961)	(7.153)
Constant	0.205***	0.121
	(0.033)	(0.081)
Observations	121	121
R^2	0.111	0.027
Adjusted R^2	0.096	0.010
Residual Std. Error (df = 118)	0.033	0.079
F Statistic (df = 2; 118)	7.336***	1.629
Note:	*p<0.1; **p<0.05; ***p<0.01	

Answer: This approach using two separate regressions returns the exact same point estimates (though the standard errors are different).

6 Yet another IV trick: Taking the "Good" variation and scaling it

6.1 Question: Take the coefficient from you reduced form estimate and divide it by your first stage estimate. How does this value compare your earlier estimate for the main result?

Answer:

The coefficient from my reduced form estimate is -0.070 for white poverty and 0.092 for black poverty. The coefficient for the first stage is 0.357. We thus get -0.196 and 0.258, the same as our earlier point estimates.

7 Submission instructions:

1) Knit your assignment in PDF.
2) Make sure you have ONE question and answer per page unless a question spans two pages where noted (this allows gradescope to easily find your answers). It should be 24 pages.
3) Upload your assignment PDF to gradescope.