# ASAP Assignment 2

Angelo Barisano; 508903

September 23rd, 2022

# 1 Difference in Difference

## 1.1 Task 1: Derive Diff-In-Diff Coefficients

$(1-1)$ $y_{it} = \beta_0 + \beta_1 D_i + \beta_2 T_t + \beta_3 D_i T_t + \epsilon_{it}$

Considering the canonical difference-in-difference equation expressed in regression form (1-1), the individaul outcome of $y_{it}$ is defined by five terms:

1. $\beta_0$; constant - will be cancelled out in later part
2. $\beta_1 D_i$; treatment indicator - whether the subject is treated or not represented by either (D= 1|D = 0)
3. $\beta_2 T_t$; independent of the subject, the "event study" contains pre- and post-test measurements indicator for each subject
4. $\beta_3 D_i T_t$; the interaction effect of the treatment indicator and the time indicator displays the assumed effect of the change from pre to post test in $T_t$ for an individual in the treatment or control - in case of treatment, this term falls out as the general assumtion of diff-in-diff pertains to the control being the same as the treatment.
5. $\epsilon_{it}$; contains the disturbances

The terms in 2, 3, & 4 are relevant in describing the potential outcome assumption in difference in difference analysis. Difference in difference suggests that we compare the difference between treatment and control before and after the treatment introduction (t = 0), shown as:

$(1-2)$ $[E(y_{T=1}|D=1) - E(y_{T=0}|D=1)] - [E(y_{T=1}|D=0) - E(y_{T=0}|D=0)]$

Subsequetnly, the four outcomes described in (1-2) yield the following outcomes:

- $E = (y_{T=1}|D=1)$; Becasue we are observing the outcome for the post-(treatment) test for treatment group, this yields $\beta_0$, $\beta_1$, $\beta_2$, $\beta_3$
- $E = (y_{T=0}|D=1)$; Because we are observing the outcome of the pre-(intervention) test for the treatment, this will yield $\beta_0$, $\beta_1$
- $E = (y_{T=1}|D=0)$; Becasue we are observing the outcome for the post-(treatment) test for the control group, this yields $\beta_0$, $\beta_2$
- $E = (y_{T=0}|D=0)$; Because we are observing the outcome of the pre-(intervention) test for the control, this will yield $\beta_0$

Note that the disturbance term is left out as it is assumed to be independent of the treatment selection etc.; as such we will ignore it here. Additionally, the constant is present in all four outcomes; thus, it also cncels out in the following equation. This originates from the assumption that the covariates measurments in pre and post test yield the same results for both treatment and control subjects. Equivalently, by substitution the aforementioned outcomes into (1-2), the following results can be deduced:

$(1-3)$ $E(y_{it}) = [E(y_{T=1}|D=1) - E(y_{T=0}|D=1)] - [E(y_{T=1}|D=0) - E(y_{T=0}|D=0)]$

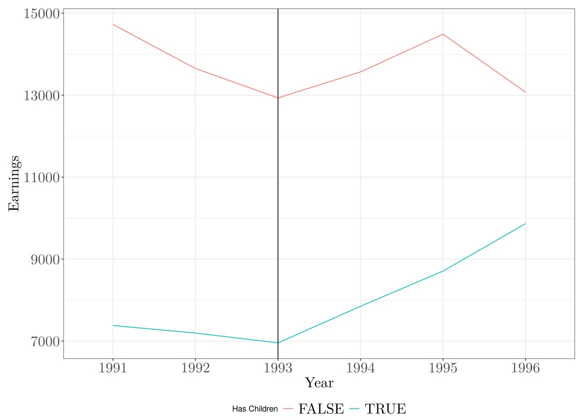
$(=)$ $E(y_{it}) = [(\beta_1 + \beta_2 + \beta_3) - (\beta_1)] - [(\beta_2)]$

$(=)$ $E(y_{it}) = (\beta_2 + \beta_3) - \beta_2 = \beta_3$

**NOte possibly delete duplicates**

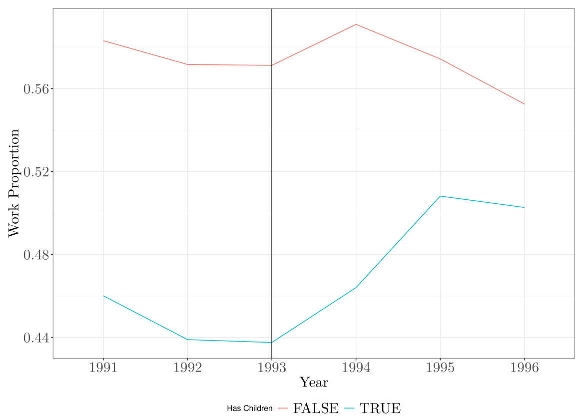
Important: we canot identify the monthrs; so If they become mothers at some point, we will assume that these are taken out!

## 1.2 Task 2: Provice Graphical "evidence" for the presence of the DiD effect




(a) Annual Earnings by Females with(out) Children


(b) Family Earnings Earnings by Females with(out) Children




(c) Work Participation by Females with(out) Children

Figure 1: Pre-Post Intervention of EICT Credit for Women with(out) Children

Figure 1 displays the outcomes for both treatment and control group for earnings (earn), family income (finc), and work-participation indicator (work) over the period form 1991 to 1996. THe treatment in this case is defined as a binary state of Females with children (one or many) (D = 1) and females without children (D = 0).[1]. The tax credit (EITC) is assumed to be introduced on the 1st of January 1993.[2] Figure 1 a) displays the development of earnings and the introduction of the EITC is marked by the vertical line (as in the other graphics). Females without children earned considerably more on average than females with children, starting out at slightly less than \$14800 and dropping to \$13000 at its lowest. Overall, both groups displayed a downward trend before 1993. After 1993, the supposed introduction of the EITC, both groups experienced an increase in earnings; However, the childless group did not display a continous increase in earnings when compared to females with children, which displayed a continous increase of earnings after the introduction. This might suggest that the introduction of the EITC is associated to the average earnings of women with children but not for women without children. Figure 1 b) shows the same features as the plot before but the outcome is now Family Income. Overall, the point of origin general trend is similar for both groups as in Figure 1 a); it may be noted that the trend for females with child is less pronounced than in a). Thus, the conclusion is the same as in a): an overall positive trend is displayed for females with children, while childless females do not improve considerably during the post period. Figure 1 c) displays workparticipation of females with and without children.Again, childless women start out higher at around 54% workparticipation vs 46% workparticipation for women with children. Moreover, the trends are somewhat comparable to the two preceeding graphics, as females with children display an increase to 50.3% (and then a slight drop in the following year), while childless women tend to decrease. Thus, on average during the post treatment period, we see a substantial increase for women with children in workparticipation.

1. Describe each picture and what you can see; but also note that this is based on averages and not statistically true

[1] I do refer to females/ males as the study subject in question

[2] see canvas discussion board

2. IMPORTANT: you should look at the grading grid of the previous assignment to see what their requirements are for these

## 1.3 Task 3: Summary Statistics for data

The dataset is not balanced and we cannot assure that it is fixed. Nonetheless, for the purpose of this exercise, it is assumed that it is balanced and fixed. The data contains yearly records from 1991 to 1996; the reported values per variable are thus averages over all six years. A total of 13746 records were made, split by year into 2610, 2449, 2342, 2255, and 2085 observations respectively. Of the total 13746 observations, 7819 have one or more children, and 5927 has no children.[3]. Of the relevant outcome variables (earnings, family income, work participation), the average family income was \$15255.32 ($std$ = 19444.24, $median$ = 9636.66). This large spread around the mean was partially addressed by Figure 1 a) displaying a large difference between women with and without children; this suggests a strong heterogenity in the data wrt. to the outcomes. Additionally, as was to be expected by the financial nature of family income, there is a severe positive skewness of 7.06. Earnings displays a similar pattern as family income ($mean$ = 10432.48, $std$ = 18200.76, $median$ = 3332.18 $skew$ = 6.766), which is supported by Figure 1 b). As expected, earnings and family income correlate strongly with a Pearson correlation coefficient of .93 ($p < 0.001$); thus, earnings and family income are assumed to behave similarly as outcome variables. Finally, work participation shows that 51.3% of records over all six years are in employment (std. and median have no meaning here as it is a binary variable). Considering possible covariates, the average years in education is 8.8 ($std$ = 2.636), with 11 years in the median. On average, per year, one women had 1.19 children ($std$ = 1.382, $median$ = 1), with 56.9% of respondents having one child or more (N = 7819). Of the respondents 60% were people of colour. Unemployment rate by state was on average 6.76% ($std$ = 1.462, $median$ = 7.7) and unearned income at \$4823 ($std$ = 7123, $median$ = 6864)

Table 1: Descriptive Statistics of Numeric Indepdenent and Dependent Varaible

| Statistic | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| urate | 6.762 | 1.462 | 2.600 | 5.700 | 6.800 | 7.700 | 11.400 |
| children | 1.193 | 1.382 | 0 | 0 | 1 | 2 | 9 |
| finc | 15,255.320 | 19,444.250 | 0.000 | 5,123.418 | 9,636.664 | 18,659.180 | 575,616.800 |
| earn | 10,432.480 | 18,200.760 | 0.000 | 0.000 | 3,332.180 | 14,321.220 | 537,880.600 |
| age | 35.210 | 10.157 | 20 | 26 | 34 | 44 | 54 |
| ed | 8.806 | 2.636 | 0 | 7 | 10 | 11 | 11 |
| work | 0.513 | 0.500 | 0 | 0 | 1 | 1 | 1 |
| unearn | 4.823 | 7.123 | 0.000 | 0.000 | 2.973 | 6.864 | 134.058 |
| has_children | 0.569 | 0.495 | 0 | 0 | 1 | 1 | 1 |
| dperiod | 1.632 | 0.482 | 1 | 1 | 2 | 2 | 2 |

*Notes:* N = 13746

## 1.4 Task 4: Matrix Diff in Diff

Table 2 reports the simply pre-post intervention averages for the two groups - Women with children and women without children - for earnings, family income, and work participation proportion. As shown in Figure 1 a) childless women have on average higher earnings in both pre- and post period than women with children. However, only women with children show a positive average gain over the post intervention period of \$986.82, when compared to the average over the pre treatment period, while childless women even drop in earnings in the post period. using formula (1-2) his results in a *naive* DiD effect of \$1682.82 for women with children.[4] Again, a similar observation can be made for family income which displays a DiD of \$1911.04. Finally, worp participation also followed the trend observed in Figure 1 c), suggesting a DiD effect of 0.04 (or 4% point gain ov women with children over childless women). However, the aforementioned results are not signigicatn, as no formal test was conducted. Additionally, the results do not suggest causality - it only suggests a tendency. NOte: this does not suggest any causailty

[3]additional summary statistics can be found for women with and without children in Appendix 4.1

[4]This utilizes the aforementioned formula of $[E(y_{T=1}|D = 1) - E(y_{T=0}|D = 1)] - [E(y_{T=1}|D = 0) - E(y_{T=0}|D = 0)]$

Table 2: Diff-in-Diff Matrix

| | | Earning | | Family Income | | Work Participation | |
|---|---|---|---|---|---|---|---|
| | dperiod | Childless | Children | Childless | Children | Childless | Children |
| Before | 1 | 14,203.900 | 7,290.380 | 19,159.190 | 12,140.900 | 0.580 | 0.450 |
| After | 2 | 13,507.900 | 8,277.200 | 18,218.950 | 13,111.690 | 0.570 | 0.480 |
| Difference | | -696.000 | 986.810 | -940.240 | 970.800 | -0.010 | 0.030 |

*Notes:* N = 5927 Childless; N = 7819 Has one or more Children

### 1.5 Task 5: Analyze the DiD effect with appropriate regression models for the three dependent variables

**Control Varaibles and covariates** WHICH VARIABLES ARE ASSUMED TO HAVE AN IMPACT?

**REMEMBER WE DO NOT RUN LOG AS WE ARE INTERESTED NOT IN COMPARING BUT RATHER IN LOOKING AT THE EFFFECT OF ONE VARIABLE!! SO WE DO NOT LOG SCALE TO MAKE IT INTERPRETABLE**

1. ADD A LITTLE THEORY WHY YOU ADD EACH CONTROL VAIRABLE into each model for each dependent variable! this is important: so put some effort into arguing why to include eg UNEMPLOYMENT rate into the equation of earnings (a good arugment would be: high unemployment means more people searching jobs means wage suppression ; a simple demand and suply rule)

2. create an example table that reports exactly the same as that one above, but here the SEs are robust!!! for clustered on state and white; they will not really differ so also report the breusch pagan test here

3. RUN BREUSCH PAGAN OFR EACH MODEL

**NOTE STANDARDIZED COEFFICIENTS ARE NOT REPORTED AS THEY ARE USELESS IN THIS CONTEXT; WE ARE NOT LOOKIGN FOR EFFECT SIZE BUT RATHER THE CASE OF**

**Note:standardized coefficinets will NOT be included as they are of no interpretable interest here and there is no real effect size we want to estimate in the first place.**

**Also: give a short theroy for why control variables were included! LOOK AT PQRM QUANTITATIVE CORUSE AT UVA; THEY CALLED IT SOMETHING SPECIAL!**

**IMPORTANT: EXPLAIN WHY IN CERTAIN MODELS THE CONTROL VARIABLES WORK AND WHY THEY DONT WORK IN OTHER MODELS!! Build a theory in this regard**

**NOTE ROBUST STANDARD ERROS MIGHT NOT EVEN BE NEEDED IN THIS CASE DUE TO THE THEORY BEHIND DIFF IN DIFF**

**NOTE: WRITE A THEORY FOR EACH CONTROL VARIBALE REGARDING EACH DEPEDNET: EG THE urate may not ahve a controllign effect on earnings but it may have on family income**

Table 3: Non-Robust Regression Results Part 3

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | earn | | finc | | work | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Constant | 14,899.900*** | 12,958.640*** | 20,099.430*** | 16,218.430*** | 0.582*** | 0.532*** |
| | (828.375) | (1,550.012) | (886.522) | (1,655.347) | (0.023) | (0.043) |
| has_children1 | −8,596.327*** | −8,394.973*** | −8,929.330*** | −8,269.567*** | −0.159*** | −0.150*** |
| | (1,093.444) | (1,096.506) | (1,170.197) | (1,171.022) | (0.030) | (0.030) |
| dperiod | −695.997 | −536.491 | −940.239* | −515.553 | −0.005 | −0.024* |
| | (485.413) | (500.046) | (519.486) | (534.028) | (0.013) | (0.014) |
| age | | 22.555 | | 78.717*** | | 0.002*** |
| | | (15.922) | | (17.004) | | (0.0004) |
| urate | | 133.948 | | 372.861*** | | −0.018*** |
| | | (114.614) | | (122.403) | | (0.003) |
| ed | | 66.337 | | −125.305** | | 0.017*** |
| | | (59.579) | | (63.628) | | (0.002) |
| nonwhite1 | | −1,255.622*** | | −2,438.387*** | | −0.043*** |
| | | (326.237) | | (348.408) | | (0.009) |
| has_children1:dperiod | 1,682.810*** | 1,722.360*** | 1,911.035*** | 2,006.060*** | 0.031* | 0.033* |
| | (642.099) | (641.893) | (687.171) | (685.515) | (0.018) | (0.018) |
| $R^2$ | 0.026 | 0.027 | 0.022 | 0.028 | 0.012 | 0.027 |
| Adjusted $R^2$ | 0.026 | 0.027 | 0.022 | 0.027 | 0.012 | 0.026 |
| Residual Std. Error | 17,965.670 | 17,956.450 | 19,226.750 | 19,176.730 | 0.497 | 0.493 |
| F Statistic | 121.691*** | 54.794*** | 105.245*** | 56.166*** | 54.906*** | 54.374*** |

*Note:* N = 13746. Non Robust Standard Errors applied. "White" is reference category for "non-White" categorical variable.

**IMPORTANT: RUN BREUSCH PAGAN OFR EACH MODEL**

## 1.6 Task 6: Subset analysis

**REMEMBER WE DO NOT RUN LOG AS WE ARE INTERESTED NOT IN COMPARING BUT RATHER IN LOOKING AT THE EFFFECT OF ONE VARIABLE!! SO WE DO NOT LOG SCALE TO MAKE IT INTERPRETABLE**

**NOTE: IN THIS CASE WE USE THE SUBSET ANALYSIS and not use interactions due to the efficeincy; if we were to use interactions, the analysis would have a higher statistical power, but the problem is: it would be really difficult to discern**

**NOTE WE STILL USE DIFF IN DIFF BECAUSE WE STILL WANT TO SEE THE EFFECT OF THE POLICY INTERVATION JUST HERE SUBSECTIONED BY DIFFERENT VARIABLES**

**GENERAL ASSUMTION: ALL WOMEN ARE SINGLE WOMEN IN THE DATA SET**

**WE ARE LOOKING AT THE POLICY EFFECT OF INTROUDCING THE TAX CREDIT WHEN CONSIDERING THE SUBSET OF WOMEN WITH CHILDREN and SUBsection HIGH vs low eduction**

**IMPORTANT: UPDATE THE TABLES AS YOU DID NOT UPDATE THE STARGAZER AFTER THAT ONE!!!**

### 1.6.1 Women with Children compared based on high & low education levels

1. report the same insight as you did during class!
2. IMPORTANT: CHECK AND CALCULATE THE TABLE CONTENTS AGAIN! THERE MIGHT BE SOME NUMBERS OFF!!

### 1.6.2 Women with and without Children compared keeping education level (low) constant

Table 4: Subsection Analysis Single Women with Children for alternating low/ high education levels

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | earn | | finc | | work | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Constant | 5,316.131*** | 1,448.297 | 10,126.090*** | 1,096.734 | 0.424*** | 0.533*** |
| | (701.736) | (1,409.668) | (738.891) | (1,473.471) | (0.023) | (0.047) |
| edu_lvllow | 3,427.529*** | 3,177.416** | 3,629.042*** | 3,079.124** | −0.002 | −0.006 |
| | (1,311.705) | (1,306.105) | (1,381.156) | (1,365.220) | (0.044) | (0.044) |
| dperiod | 1,241.689*** | 1,368.092*** | 1,308.968*** | 1,799.017*** | 0.032** | 0.010 |
| | (413.039) | (432.758) | (434.908) | (452.345) | (0.014) | (0.014) |
| age | | 174.206*** | | 272.964*** | | 0.004*** |
| | | (20.082) | | (20.991) | | (0.001) |
| urate | | −34.414 | | 261.583** | | −0.025*** |
| | | (127.034) | | (132.784) | | (0.004) |
| nonwhite1 | | −2,547.489*** | | −3,380.644*** | | −0.061*** |
| | | (368.752) | | (385.442) | | (0.012) |
| edu_lvllow:dperiod | −871.461 | −951.502 | −1,166.212 | −1,345.136* | −0.021 | −0.019 |
| | (773.065) | (767.593) | (813.996) | (802.335) | (0.026) | (0.026) |
| Observations | 7,819 | 7,819 | 7,819 | 7,819 | 7,819 | 7,819 |
| $R^2$ | 0.005 | 0.020 | 0.004 | 0.033 | 0.002 | 0.016 |
| Adjusted $R^2$ | 0.004 | 0.020 | 0.003 | 0.033 | 0.001 | 0.016 |
| Residual Std. Error | 14,923.420 | 14,810.030 | 15,713.570 | 15,480.340 | 0.499 | 0.495 |
| F Statistic | 12.717*** | 26.977*** | 9.460*** | 44.915*** | 4.884*** | 21.557*** |

*Note:* N = 7819 Single Women have Children. N = 5593 high education (years of eduction >= 9 years); N = 2226 low education (years of eduction < 9 years); Non Robust Standard Errors applied. "White" is reference category for "non-White" categorical variable.

Table 5: Subsection Analysis Single Women with/ without Children for constant (low) education levels

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | earn | | finc | | work | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Constant | 11,066.700*** | 4,281.758 | 17,494.530*** | 8,507.214*** | 0.501*** | 0.441*** |
| | (1,457.343) | (2,602.848) | (1,534.185) | (2,735.084) | (0.038) | (0.068) |
| has_children1 | −2,323.038 | −2,402.722 | −3,739.399* | −3,267.950 | −0.080 | −0.087 |
| | (2,026.514) | (2,030.169) | (2,133.367) | (2,133.311) | (0.053) | (0.053) |
| dperiod | 783.677 | 1,378.102 | 322.393 | 1,127.629 | −0.004 | −0.007 |
| | (858.662) | (882.127) | (903.937) | (926.943) | (0.023) | (0.023) |
| age | | 29.868 | | 83.479*** | | 0.001 |
| | | (29.856) | | (31.373) | | (0.001) |
| urate | | 651.163*** | | 845.832*** | | −0.002 |
| | | (216.731) | | (227.742) | | (0.006) |
| nonwhite1 | | 332.812 | | −2,403.220*** | | 0.081*** |
| | | (664.392) | | (698.146) | | (0.017) |
| has_children1:dperiod | −413.449 | −475.403 | −179.637 | −152.761 | 0.015 | 0.012 |
| | (1,194.473) | (1,193.612) | (1,257.455) | (1,254.253) | (0.031) | (0.031) |
| Observations | 4,311 | 4,311 | 4,311 | 4,311 | 4,311 | 4,311 |
| $R^2$ | 0.006 | 0.009 | 0.010 | 0.016 | 0.003 | 0.008 |
| Adjusted $R^2$ | 0.006 | 0.008 | 0.009 | 0.015 | 0.002 | 0.007 |
| Residual Std. Error | 18,962.540 | 18,944.100 | 19,962.390 | 19,906.540 | 0.498 | 0.497 |
| F Statistic | 9.304*** | 6.559*** | 14.690*** | 11.920*** | 4.494*** | 6.121*** |

*Note:* N = 4311 Single Women have Children (years of eduction < 9 years). N = 2085 has no children; N = 2226 has children; Non Robust Standard Errors applied. "White" is reference category for "non-White" categorical variable.

# 2 Tart 2 Instrumental Variable approach

Notes: - Effect of cumpulsory schooling on wages

Generaly: the quality and quantitiy of education in modern societies is on a steady rise; but it is difficult how much education contributes to future earnings on the labor market.. meansing: how much does one year of additional education add in earnings

This is because of unobserved factors that are to the detrimetn of assumtion 3 (mean independence) biasing any OLS estimate of wages on years of eduction (ommitted variables and confounders).

Here the solution: instruments to circumvent these biases; combining to characteristics: −¿ Minimum legal school dropout age (which can be 16, 17, or 18 years) −¿ and the annual quarter of birth of a person

Rational behind these choices: all students born in the sam year are admitted to school in the same cohort (the same class). BUT A student born in eg January reaches the leagal school dropout age earlier than a student born in September 8eg).

−¿ as such, the instruments function as if; we randomize school exposure to students, assuming that in each year, a constant fraction of students drops out of school adn this dorpout pattern is unrelated to when a students is born.

**MAIN TASK: Estimate the effect of the yerars of education on the LOG scaled wages**

## 2.1 Task 1: Explain wHY ols is biased here - A3

1. see slide 67;
2. mention that this is a 1930s during the great depression!
3. 
4. 

**mention why Years of education is endogenous**

**We therefore use geographical proximity to a college when growing up as an exogenous instrument for education**

**INCLUDE EXOGENEOUS VARIABLES AS WELL IN THE INSTRUMENTAL PART!!!**

**SLIDE 67 ff IMPORTANT SEE SLIDES 7 ff!!!.** −¿ IMPORTANT: ALSO INCLDUE 1) THE METHOD OF IV being different than least squares (it is a method look up in notes) and 2) mention the two requirements for a good Instrument: a) cleanliness no impact on outcome causally only through the biased independent varaible and b) the relevance which is high correlcion with the independent varaibvles that are instrumentalized

**In this exercies give two examples of conditions that could bias the estimated education effect if only OLS is used; This means: give examples how the variable YEARSOFEDUCATION is a biased estimator becasue mean independece is violated −¿ the example given was: students preference for education may influence how long they stay in school and how much they earn on the labor market which is simply their ambition; other factors might be: family background and societal status/ socioeconomic status which means something like teen pregnancy OR IN THE 1930s during the great depression just the need to support the family during time of need so you could not go to school**

**eg IQ is a good thing**

## 2.2 Task 2: Summary statistics for this task

1. remember to describe categorical variables in text
2. add skew and median!!

relevant quantiative variables age, educ (years of education), lnwage(weekly earnings), marrital status; quarter of birth of the recorded child; SMSA: categorical variable where someone lives (urban vs not urban); yob year of birth which is also categorical

−¿ possibly retransform lnwage to just wage by reversing the log scaling

Table 6: Instrumental Vairable Approach Descriptive Statistics of Numeric Indepdenent and Dependent Varaible

| Statistic | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Age | 44.645 | 2.940 | 40 | 42 | 45 | 47 | 50 |
| Years of Education | 12.770 | 3.281 | 0 | 12 | 12 | 15 | 20 |
| Ln(Wage) | 5.900 | 0.679 | −2.342 | 5.637 | 5.952 | 6.257 | 10.532 |

*Notes:* N = 13746; Wage is backwards transformed from lnWage

## 2.3 Task 3: Diagnositcs of Year Of Birth as instrument: is it any good?

**see slide 88; 82**

1. here already use the regression outputs from task 4 and also the a correlation table
2. add a plot!!!
3. partial f test for relevance/ strength of the instrument!
4. summary(rslt2SLS.B, diagnostics = TRUE) –¿ see the things in tutorial 2 there I descibe all of it; also the slides are relevant

**A good instrument possesses two specifications: it is clean and it is relevant**

Cleanlieness: means that the Instrument only has an impact on the outcome through the Indepdendent variable (the to be "instrumentalized" variable); this assumption cannot be tested but is rather grounded in theory (meaning that the instrument is exogeneous – obviously you cannot test exogineity)

Relevantce: Contrarily, this assumption can be tested: it states that the instrument used for the "to be instrumentalize" variable is strong, meaning that there is a relevant correlation between the instrument and the independent variables. Note: a correlation between the instrument adn the independent variables beyond the baised variable is welcome. It only becomes a problem when the instrument and the dependent varaible are related; btu there will always be some correlation in that regard. To this end, an anova is run on the two stage model in order to conduct the F test, which helps with multiple outputs: Wu-Hausman, Sargan, and F test (the former two are only relevant if the model is overidentified by the instrument)

**HOW DO I CONDUCT THESE TESTS? CAN I CONDUCT THEM ON THE NORMAL 2SLS via OLS or should I better use the IVreg model?**

## 2.4 Task 4: Conduct IVreg of the effect of effect of education on log wages, using quarter of birth as the instrument; are robust SE needed?

1. IT IS VERY IMPORTANT TO BUILD A QUICK THEORY AND ALSO EXPLAIN WHY THE CONTROL VARIABLES ARE EXOGENOEUS; SO WHY THERE CONTROLS ARE RELEVANT!!!!!
2. also look at the examples in those links how they didd this !

**IMPORTANT: IF YOU INCLUDE CONTROL VARIABLES YOU NEED TO ARGUE WHY THEY ARE EXOGENEOUS OR NOT AS THAT THEY ARE INCLDUED INTO THE EQUATION** SLIDE 99 IMPORTANT: USE slide 88 as an argument

**IMPORTANT: WHEN YOU SAY HOW CONTROL VARIABLES IMPACT THE INDEPENDENT VARIABLE SAY THE INCLUSION OF THE CONTROL VARIABLES ICNREASE IT INTO A CERTAIN DIRECTIOn; SO DEPEDNING ON THE INSTRUMENT VS NORMAL OLS, the variable was biased eg downwards or upwards**

## 2.5 5 –

1. here we do the parital F test on the IV regression!
2. loot in the notes for this lecture to see the argument begind this f test
3. also analyse the hausman and sargan test on the same models as before; IMPORTANT THESE ARE ONLY FOR OVERIDENTIFICATION!!!

Table 7: IV REGRESSION OUTPUT

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | lnwage | | | | | |
| | *OLS* | | *instrumental variable* | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Constant | $4.995^{***}$ | $4.601^{***}$ | $4.633^{***}$ | $3.243^{***}$ | $5.892^{***}$ | $3.790^{***}$ |
| | (0.004) | (0.018) | (0.250) | (0.524) | (0.082) | (0.406) |
| educ | $0.071^{***}$ | $0.070^{***}$ | $0.099^{***}$ | $0.159^{***}$ | 0.001 | $0.123^{***}$ |
| | (0.0003) | (0.0003) | (0.020) | (0.034) | (0.006) | (0.027) |
| age | | $0.004^{***}$ | | $0.009^{***}$ | | $0.007^{***}$ |
| | | (0.0004) | | (0.002) | | (0.002) |
| married | | $0.255^{***}$ | | $0.233^{***}$ | | $0.242^{***}$ |
| | | (0.003) | | (0.009) | | (0.007) |
| Observations | 329,509 | 329,509 | 329,509 | 329,509 | 329,509 | 329,509 |
| $R^2$ | 0.117 | 0.134 | 0.098 | −0.049 | 0.002 | 0.069 |
| Adjusted $R^2$ | 0.117 | 0.134 | 0.098 | −0.049 | 0.002 | 0.069 |
| Residual Std. Error | 0.638 | 0.632 | 0.645 | 0.695 | 0.678 | 0.655 |
| F Statistic | $43{,}782.560^{***}$ | $17{,}053.180^{***}$ | | | | |

*Note:* N = HUUUUGE; so degrees of freedom are not reported for F tests

4. important: perform all these tests like in the tutorial and also part 3/4 already!!!! – report all those tests formally in one table!

**IMPORTANT: WE DO NOT INCLUDE THE INSTRUMENTS IN OLS BECASUE WE AUSSME THAT THEY DONT HAVE AN IMPACT on the outcome!!!!!! in OLS; SO DONT INCLDUE THEM IN THE OLS OTHERWISE WE GO AGAINST THE UNDERLYING THEORY SLIDE 105 perform partial F test to see whether IV reg is good or not and if it is good then it is better than OLS!**

**for overidentificaion run another IVREG WITH MORE insturments see introductiomn; then you can interpret the SARGAN AND HAUSMA TEST THINGI**

### 2.6 6 –

1. not clean insutruments! this would lead to violation of mean independence
2. weak insturments leads to mean indepdence violation as well becasue the indstruments simply do not work as they should
3. google some stuff and see internet

reasons: not clear instrument (or not clean) (make a plot; or if the instrument is not relevant or weak)

# 3 Bibliography

# 4 Appendix

## 4.1 Additional demographics

# 5 Code

Table 8: Descriptive Statistics of ECIC; With Children

| Statistic | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Family Income | 12,750.390 | 15,739.050 | 0.000 | 4,652.465 | 8,425.197 | 15,218.720 | 410,507.600 |
| Earnings | 7,909.934 | 14,956.930 | 0.000 | 0.000 | 1,110.727 | 11,107.270 | 366,095.500 |
| Age | 32.717 | 8.630 | 20 | 25 | 32 | 39 | 54 |
| Education | 9.001 | 2.408 | 0 | 7 | 10 | 11 | 11 |
| Education Years | 4.840 | 5.872 | 0.000 | 0.071 | 3.761 | 7.070 | 102.958 |
| Unearned Income | 2.097 | 1.209 | 1 | 1 | 2 | 3 | 9 |
| Count Children | 0.466 | 0.499 | 0 | 0 | 0 | 1 | 1 |

*Notes:* N = 7819

Table 9: Descriptive Statistics of ECIC; Without Children

| Statistic | Mean | St. Dev. | Min | Pctl(25) | Median | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| Family Income | 18,559.860 | 23,041.780 | 0.000 | 5,793.092 | 11,912.950 | 24,391.010 | 575,616.800 |
| Earnings | 13,760.260 | 21,301.400 | 0.000 | 0.000 | 7,664.014 | 19,447.610 | 537,880.600 |
| Age | 38.498 | 11.046 | 20 | 28 | 40 | 49 | 54 |
| Education | 8.549 | 2.889 | 0 | 7 | 10 | 11 | 11 |
| Education Years | 4.800 | 8.496 | 0.000 | 0.000 | 1.248 | 6.528 | 134.058 |
| Unearned Income | 0.000 | 0.000 | 0 | 0 | 0 | 0 | 0 |
| Count Children | 0.574 | 0.494 | 0 | 0 | 1 | 1 | 1 |

*Notes:* N = 5927