ASAP Assignment 2

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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. β_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. ϵ_{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 β_0, β_1, β_2, β_3
- $E = (y_{T=0}|D=1)$; Because we are observing the outcome of the pre-(intervention) test for the treatment, this will yield β_0, β_1
- $E = (y_{T=1}|D=0)$; Becasue we are observing the outcome for the post-(treatment) test for the control group, this yields β_0, β_2
- $E = (y_{T=0}|D=0)$; Because we are observing the outcome of the pre-(intervention) test for the control, this will yield β_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:

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

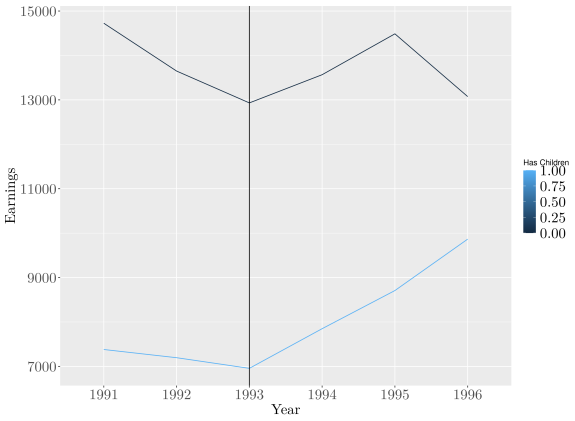
$(=)$ $E(y_{it}) = [(\beta_1 + \beta_2 + \beta_3) - (\beta_1)] - [(\beta_2)]$

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

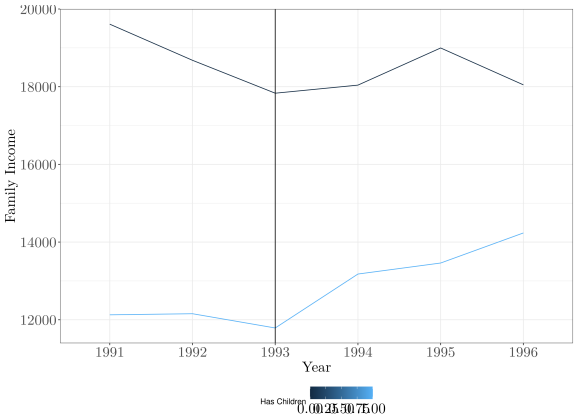
NOte possibly delete duplicates

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

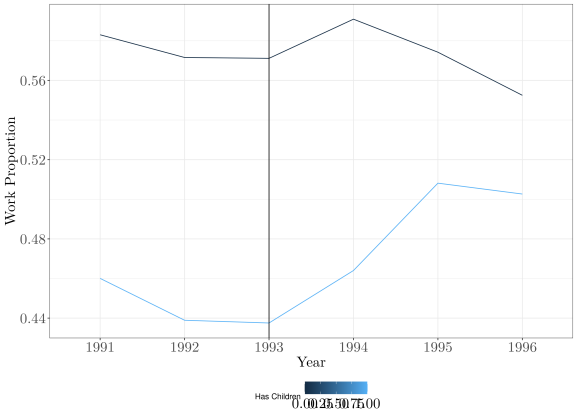
1.2 Task 2: Provice Graphical "evidence" for the presence of the DiD effect



(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 workparticipation 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: Diff in Diff Matrix

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 \$1682.81 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. **We will discuss this next.**

All observations included in any model. *** p<0.01, ** p<0.05, * p<0.1. Standardized regression coefficients are reported in the adjacent column to the model. For complementary regression models **see appendix**. The comparison category in "Zone" (IV) is "Moderate-to-High Density". Years in date range is 2006 to 2010. The Sale Price is represented in 1000s.

[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 regression

ADD POPULATION REGRESSION

Tutoial 1 plot for heteroscedasiticty fitted vs standardized residuals

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

Results Due to breviety concerns, the main findings are compiled in one table; **THE APPENDIX WILL CONTAIN FURTHER ANALYSIS THAT WILL PROVE THAT I DID THIS**. Table 3 contains models for all three outcome variables, with the first model (1, 4, 7) containing a baseline model with only covariates. Models 2, 5, 8 contain only the DiD effects, and Models 3, 6, 9 contain the full model respectively. Overall, all models display a significant F-statistic

Please note there was little need to include Standardized coefficeints as we were only interested in the DiD effect and not the comparison to other terms. Additionally, no log specification was performed as this would make the interpretation more difficult; nonlinearity did not seem to pose a large problem

Considerig earnings, the covariate model (1) shows only that nonwhite (indicator variable) ($\hat{\beta}$ = -2037.990, $p < 0.001$) and age ($\hat{\beta}$ = 96.038, $p < 0.01$) are significant. Overall, this model explains 0.6% of the variation in earnings. Proceeding to only the DiD effect (model 2), as expected, women with children earn on average \$8596.33 ($p < 0.01$) less than childess women.[5] Subsequently, the value from Table 2 for the DiD effect is statistically significant at conventional levels, suggesting that women with children gain a \$1682.81 ($p < 0.01$) in the post treatment/intervention period (1993 <) when compared to childless women; overall explaining 2.6% of the total variation in earnings. This effect is important to be examined more closely: As implied in task 4, while childless women on average earn \$ 8596.33 more than women with children, childless women (see Table 2) drop by \$696 when comparing the before and after period, while women with children increased. These two effects cancel each other out out, most likely leading to the insignificant period coefficient. Moreover, this suggests that the comparison groups (women with vs women without children) are not comparable; as such we will not be able to discern causality from this exercise. Finally, model (3) considers the full model. Focusing on the DiD effect after including covariates, we see a slight increase in the coefficient ($\hat{\beta}$ = 1722.360, $p < 0.01$) with stable standard errors; suggesting that women with children in the post period earn \$1722.36 more than childless women. However, the inclusion of the covariates does not suggest a considarable change in the direction of the outcome. Moving to family income as an outcome, a similar insights can be drawn. However, now all covariates are significant; and the model explaining 1.2% of the variation in family income. Again, the DiD effect alone in model (5) is significant ($\hat{\beta}$ = 1911.04, $p < 0.01$); suggesting again that women with childrens' familiy income increases by \$1911.04 after the intervention when compared to childess women. Additionally, women with children, again, have a lower family income of \$-8929.33 ($p < 0.01$),Interestingly, the period indicator now suggests that the overall family income drops maginally significantly ($\hat{\beta}$ = -940.24, $p < 0.1$). This model explains 2.2% of the total variation in family income. The inclusion of covariates does not change this insight dramitically; womens' with children family oincome still improve significantly during the post period when compared to childess women and its coefficeint also increases, but the insight is the same as before ($\hat{\beta}$ = 2006.06, $p < 0.01$). Finally, considering work participation; the covariates alone in model (7) are all significant at the conventional level in predicting work participation, explaining 1.9% of total variation in this outcome. As observed during task 1 through 4, work participation rises for women with children during the post intervention period (model 8) ($\hat{\beta}$ = 0.031, $p < 0.1$); however, the effect is only marinally significant. As was to be expected, women with children show a significantly lower work participation ($\hat{\beta}$ = -0.159, $p < 0.01$) when compared to childless

[5]Note: the period indicator is not really relevant in such an exercise as it just attributes to the trend overall in y

women (15.9$ less). When combining covariates and the base model in model (9), the overall trend is the same as in the aforementioned models. The coefficient for the DiD effect rises to 0.033 ($p < 0.1$), but is still only marginally significant. Thus, overall, the inclusion of the covaraites does increase the coefficints of all three DiD effects, but only marginally. This means that the overall effect, or direction of the coefficicients was not changed drastically. Moreover, the inclusion of the covariates shows that the standard errors are stable across all models, suggesting no probelm with multicollinearity.

Robustness Tests Overall, due to the standard errrors between the models for each outcome variable respectively staying stable, this suggests that there is generally less necessity to include robust standard errors. Running the Breusch-Pagan test on all models in Table 3 - only model (1) and model (4) (both covariate-only models) fail to reject the null hypothesis of heteroscedasitc residuals. Finally, **THE APPENDIX contains the same models just with robust standard errros and clustered by state**. Overall, the standard erros do not start flailing around, which suggests, that there is little need to use robust standard errors.

1. to do: first re run the models: the baseline model with only the control variales
2. then one model with the did effect only
3. then both together

Moreover, the standard errors are stable (do not change a lot) for all coeficcients , while the coeficients themselfes maintain their direction; indicating no problem of multicollinearity.

Table 3: Non-Robust Regression Results Part 3

	Dependent variable:								
	earn			finc			work		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	7,977.343***	14,899.900***	12,958.640***	11,872.150***	20,099.430***	16,218.430***	0.414***	0.582***	0.532***
	(1,159.632)	(828.375)	(1,550.012)	(1,234.711)	(886.522)	(1,655.347)	(0.032)	(0.023)	(0.043)
age	96.038***		22.555	144.373***		78.717***	0.003***		0.002***
	(15.489)		(15.922)	(16.492)		(17.004)	(0.0004)		(0.0004)
urate	33.433		133.948	256.102**		372.861***	−0.018***		−0.018***
	(108.495)		(114.614)	(115.519)		(122.403)	(0.003)		(0.003)
ed	8.153		66.337	−177.633***		−125.305**	0.016***		0.017***
	(60.120)		(59.579)	(64.013)		(63.628)	(0.002)		(0.002)
nonwhite1	−2,037.990***		−1,255.622***	−3,109.127***		−2,438.387***	−0.058***		−0.043***
	(323.611)		(326.237)	(344.563)		(348.408)	(0.009)		(0.009)
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)
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)
Observations	13,746	13,746	13,746	13,746	13,746	13,746	13,746	13,746	13,746
R^2	0.006	0.026	0.027	0.012	0.022	0.028	0.019	0.012	0.027
Adjusted R^2	0.006	0.026	0.027	0.012	0.022	0.027	0.018	0.012	0.026
Residual Std. Error	18,150.240	17,965.670	17,956.450	19,325.370	19,226.750	19,176.730	0.495	0.497	0.493
F Statistic	20.153***	121.691***	54.794***	43.406***	105.245***	56.166***	65.588***	54.906***	54.374***

Note: N = 13746. Non Robust Standard Errors applied. "White" is reference category for "non-White" categorical variable. *** p<0.01, ** p<0.05, * p<0.1.

1.6 Task 6: Subset analysis

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

Please note: this subsection analysis was not splti into four regression models because ofconcerns for statistical power; the itnerpretation si still the same using an intercation term. For brevity reasons, the covariate only models are left (intuition does not change when comapred to table 3). Considering now only women with children and the "differences in groups" as women with high vs low education, table 4 reports a baseline and a complete model per outcome. The comparison group is low education women with children. **NOTE: all models are F statistic significant! but then there is nothing going on**

Considering earnings, (model 1 & 2), the DiD coefficient is interpreted as follows: during the post intervention period, high educated women gain 951.50$ on average ($p = 0.216$) compared to low educated women; which however is not significant. This is broadly maintained when only considering the base model ($\hat{\beta} = 871.46$, $p < 0.26$). A similar observation can be made for work participation, which is in both cases, the base model (5) and with covaraites (6), displaying an insignificant decrease in work participation for highly educated women in the post intervention period ($\hat{\beta}$ = -0.019, $p = 0.462$). Finally, family income observed a marginally significant increase of $1345.12 at the 9.4% percent level for highly educated women, while the base model is insignificant at the 15.2% level for the DiD effect of education and intervention period.

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	8,743.660***	4,625.713***	13,755.130***	4,175.858**	0.422***	0.527***
	(1,108.213)	(1,691.462)	(1,166.890)	(1,768.019)	(0.037)	(0.057)
edu_lvl	−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	370.227	416.590	142.756	453.880	0.011	−0.009
	(653.474)	(658.753)	(688.073)	(688.568)	(0.022)	(0.022)
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_lvl: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. *** p<0.01, ** p<0.05, * p<0.1.

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

Considering now only low educated women; alternating again on whether a women has a child or not, the instights are to be found in Table 5. The subsection analysis shows that the post intervention period earnings for low educated women with children decrease by $413.45 when compared to women without children in the base model; however all insignficant ($p = 0.730$). This does not change for the complete

model ($\hat{\beta}$ = -475.403, $p < 0.691$). Same can be observed for the outcome variables Family Income (main model: $\hat{\beta}$ = -179.637, $p = 0.887$) and work paticipation (main model: $\hat{\beta} = 0.012$, $p = 0.702$). Thus, there is no statistical support that work participation rises by 1.2% for women with children compared to childless women during the post intervention period and likewise for family income decreases.[6]

1.7 Conclusion subsections

Overall, the introduction of the tax credit does not seem to be significant across the different outcoems and subgroups.

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. *** p<0.01, ** p<0.05, * p<0.1.

[6] this would have been very interesting; becasue if work would go up significantly while income drops, this would be crazy.

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: Endogineity problems and correlation with u - A3

When considering the problem of mean independence (A3), there can be multiple root causes to this issue; ommitted variable bias, endogegenous treatment, sampling bias, attrition bais, simultaneous caulsailty bias. All of these issues introduce backdoor pathways **CITE ECI HERE**, which bias the (eg. OLS) estimate severely. A prominent example in what way education effect on earnings could be biased is through an ommitted varaible or covariate. A classical example for this is general ability (commonly referred to as IQ - which was introduced in 1917 already), which commonly determines not only the degree of success in education, but also future earnings. Thus, neglecting to include this confounder, will lead to a biased estimate of the effect of years of education on earnings. A second example, admittetdly a bit constructed; but this is an exercise; is higher education means higher earnings. But in the US of the 1930s, private education might have been a thing. Thus, people with higher earnings obtain more education which then goes back and forth - simultaneous causality bias. Finally, selection bias might be a problem: if we disproportionally select our sample in university cities, this will ineviably lead to bias the results, as the effect of a universtiy education usually disproportionally outweights the effect of lets say primary school years in the job market.

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

Table 6 contains the descriptive statistics of the numeric variables. overall 329,509 observations are in the data on people born between 1930 and 1939. The age range of study subectes ranges from 40 to 50, with a median age at 45 ($mean$ = 44.645, std = 2.940). The average years of education was 12.77 (std = 3.281, $median$ = 12). Finally, for interpretation purposes here, lnwage ($mean$ = 5.90, std = 0.679, $median$ = 6.257)[7] was rescaled to wage, which displayed a strong positive skew of 26.39, mean of $439.47 ($std$ = 364.941) and a median of $521.85. the log scaled wage will be used during the analysis. Moreover, 86.3% of respondents were married. SMSA indicates whether a study subject lives in rural or urban areas. Quarter of birth, the IV, distributes reasonably equally, with Q1 N = 81671, Q2 N = 80138, Q3 N = 86856, and Q4 N = 80844; it is influencial to when a study subject will start schooling; eg. suggesting that subjects from the fourth quarter generally obtain more years of study.

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
educ	12.770	3.281	0	12	12	15	20
lnwage	5.900	0.679	−2.342	5.637	5.952	6.257	10.532
married	0.863	0.344	0	1	1	1	1
qob	2.506	1.112	1	2	3	3	4
SMSA	0.186	0.389	0	0	0	0	1
yob	1,934.603	2.905	1,930	1,932	1,935	1,937	1,939
wage	439.471	364.941	0.096	280.481	384.711	521.848	37,499.990

Notes: N = 329,509; Wage is backwards transformed from lnWage

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

We can also do the partial F test here. But we do it manually iwth an OLS

1. to do: interpret the regression from table 7
2. add a plot!!! groub by year: each year gets a qob average years of education ; the foruth quarter should be higher than all others on average
3. also do the pearson correlatipon between qob and years of education
4. summary(rslt2SLS.B, diagnostics = TRUE) –¿ also refer to the diagnostics from part 4!
5. **see slide 88; 82**

A suitable instrument fulfills two conditions: 1) Cleanliness; meaining that the instrument only has an impact on the outcome thorugh the causal variable (here years of education). This assumtion cannot be tested, but is commonly based in theory. 2) The instrument is relevant, meaning that the instrument strongly predicts/ correlates with the causal ("to be instrumentalized") variable. This assumption can be fulfilled thorugh conducting an F test on the two stage model. In order to assess the relevance of the instrument statisically, one regresses the casual variable on the instrument and exogenous covariates - i.e. the first stage of the 2SLS (this can also be retrieved from the 2SLS function in R - we just demonstrate

[7] Not really interesting or relevant to display in summary statstics

it here).[8] Table 7 contains both quarter of birth as a factor and quantitaitve variable. **First of all, all models are** COnsidering first the basis models (1 & 3) without the inclusion of the covariates, one can observe for quarter of birth (qub) as a numeric (model 1), that it significantly predicts years of education ($\hat{\beta} = 0.052$, $p < 0.01$) at conventional levels. Similarly, quarter two to four are all significantly different from quarter one (Q2: $\hat{\beta} = 0.057$, $p < 0.01$; Q3: $\hat{\beta} = 0.117$, $p < 0.01$; Q4: $\hat{\beta} = 0.151$, $p < 0.01$); Similarly, this can be also observed when alteranting the catgory of comparison for quarter. Considering the relevance of qob when combined with covariates (model 2 &3), a similar picutre can be observed. It is assumed that the covaraites are exogenoeus. Interpreted as a numberic variable, qob is sifnificant at conventional levels in predicting years of education ($\hat{\beta} = 0.032$, $p < 0.01$). In model (4), most categories are also significantly different from the first quarter in years of education (Q2: $\hat{\beta}$ = -0.004, $p = 0.812$; Q3: $\hat{\beta} = 0.052$, $p < 0.01$; Q4: $\hat{\beta} = 0.088$, $p < 0.01$). Statistically, it can be asusmed qob is a relevant instrument.

Furthmore, when considering the graph one can see that on average, Q4 and Q3 tend to have more years of education than Q1 and Q2; this implicitly also might explain the aforementioend results regarding Q2 difference to Q1 in model (4) in table 7. IMPORTANT ADD CORRELATION Overall, the instrument is assumed to meet the relevance criterion; and regarding the cleanliness, this is difficult; but it is likely that qob only effects earnings through the causal variable, years of education.

Considering both basis models (1) & (3) we can observe that all coefficients for the quarter of birth is significant at the 1% level.

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)

Table 7: First Stage regression output - Relevancy

	Dependent variable:			
	educ			
	(1)	(2)	(3)	(4)
Constant	12.641***	15.150***	12.688***	15.213***
	(0.014)	(0.091)	(0.011)	(0.091)
qob	0.052***	0.032***		
	(0.005)	(0.005)		
age		−0.060***		−0.060***
		(0.002)		(0.002)
married		0.248***		0.248***
		(0.017)		(0.017)
qob_fac2			0.057***	−0.004
			(0.016)	(0.016)
qob_fac3			0.117***	0.052***
			(0.016)	(0.016)
qob_fac4			0.151***	0.088***
			(0.016)	(0.016)
Observations	329,509	329,509	329,509	329,509
R^2	0.0003	0.004	0.0003	0.004
Adjusted R^2	0.0003	0.004	0.0003	0.004
Residual Std. Error	3.281	3.275	3.281	3.275
F Statistic	100.653***	414.645***	34.009***	249.859***

Note: N = HUUUUGE; so degrees of freedom are not reported for F tests; *** p<0.01, ** p<0.05, * p<0.1

see slide 88; 82

[8] Note: in this case we perform this manually

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
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?

$NOTEFORTASK4: testwhetherusingqobasfactorworksdifferentlywhenyouonlyincludethe3dummiesforitinstaeadc$

For the purpose of this analysis, it is assumed that the control variables are all exogenoeus. Table 8 reports the corresponding outputs; model (1) and (3) consider qob as a numeric variable and model (2) and (4) consider it as a categorical variable. It may be noted that qob should be interpreted as a categorical variable to be precise. Models (5) and (6) consider an additional instrument (discussed in part 5). The control variables chosen are SMSA and whether married or not. Married was included because the proportion of married men tends to be higher for higher educated men, suggesting more education but also more income. Moreover, SMSA indicates whether a person lives in a rural or urban surrounding; people in urban areas may have better access to education and better work opportunities. Considering model (3) and (4), the causal variable education is significant (model 3: $\hat{\beta} = 0.099$, $p < 0.01$; model 4: $\hat{\beta} = 0.103$, $p < 0.01$). Considering for instance qob as a categorical IV, (model 4) we can see that if education increases by one year wage increases by 10.2%. Moving to model (5 / 6) we can also see that the choice between qob as numeric or category seems to have little effect on the general statement. COnsidering model (6), which contains SMSA and married as exogenous controls, the direction and magnitude, in addition to reported standard errors, for years of education do not change considerably when compared to model (4) (both qob as factor IV) ($\hat{\beta} = 0.100$, $p < 0.01$). Meaning, that an increase by one year in years of education is associated with a 10% higher wage. ALso the control variables are significant which are both categoricals (SMSA comparison category is rural; married comparison category is not maried) (SMSA: $\hat{\beta}$ = -0.148, $p < 0.01$; married: $\hat{\beta}$ = -0.255, $p < 0.01$); However, due to them being controls, we refrain from interpreting them here as we did with education.

TO DO: Include PLOT AND BPAGAN TEST INFERENCE HERE **ROBUST STANDARD ERRORS!!!**

Table 8: IV REGRESSION OUTPUT

	Dependent variable:					
	lnwage					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	4.633***	4.590***	4.461***	4.425***	5.514***	5.511***
	(0.250)	(0.249)	(0.249)	(0.248)	(0.076)	(0.076)
educ	0.099***	0.103***	0.098***	0.100***	0.015**	0.015**
	(0.020)	(0.020)	(0.020)	(0.019)	(0.006)	(0.006)
SMSA			−0.151***	−0.148***	−0.243***	−0.243***
			(0.022)	(0.022)	(0.007)	(0.007)
married			0.256***	0.255***	0.280***	0.280***
			(0.006)	(0.006)	(0.004)	(0.004)
Observations	329,509	329,509	329,509	329,509	329,509	329,509
R^2	0.098	0.094	0.124	0.120	0.082	0.083
Adjusted R^2	0.098	0.094	0.124	0.120	0.082	0.083
Residual Std. Error	0.645	0.646	0.635	0.637	0.650	0.650

Note: N = HUUUUGE; so degrees of freedom are not reported for F tests. *** p<0.01, ** p<0.05, * p<0.1.

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 –

Table 9: IV REGRESSION OUTPUT

	Dependent variable:					
	lnwage					
	OLS (1)	OLS (2)	HandIVREG(3)	HandIVREG(4)	HandIVREG(5)	HandIVREG(6)
Constant	4.995^{***}	4.847^{***}	4.633^{***}	4.461^{***}	4.590^{***}	4.425^{***}
	(0.004)	(0.005)	(0.263)	(0.260)	(0.262)	(0.259)
educ	0.071^{***}	0.067^{***}				
	(0.0003)	(0.0003)				
SMSA		-0.185^{***}		-0.151^{***}		-0.148^{***}
		(0.003)		(0.023)		(0.023)
married		0.265^{***}		0.256^{***}		0.255^{***}
		(0.003)		(0.007)		(0.007)
educ.hat			0.099^{***}	0.098^{***}	0.103^{***}	0.100^{***}
			(0.021)	(0.020)	(0.020)	(0.020)
Observations	329,509	329,509	329,509	329,509	329,509	329,509
R^2	0.117	0.145	0.0001	0.041	0.0001	0.041
Adjusted R^2	0.117	0.145	0.0001	0.041	0.0001	0.041
Residual Std. Error	0.638	0.628	0.679	0.665	0.679	0.665
F Statistic	$43{,}782.560^{***}$	$18{,}646.640^{***}$	23.145^{***}	$4{,}738.984^{***}$	25.088^{***}	$4{,}739.535^{***}$

Note: ALL ARE IV REGRESSION OUTPUTS!!! tests. *** p<0.01, ** p<0.05, * p<0.1.

Note: this question was not particularly precise wrt. whether to run a manual 2SLS or just normal OLS.

Model (1) and (2) in Table 9 report the OLS regressions of lnwage on the endogeneous education with and without covariates. Models (3) and (4) report the manual 2SLS for quarter of birth as a numeric. Models (5) and (6) report quarter of birth as a factor.

Considering model (2), standard OLS with covaraiates, the overall effect of education on is significantly positie ($\hat{\beta} = 0.067$, $p < 0.01$), which does not deviate drasically from its (assumed) exogeneous counterpart in the other models in Table 8 (and 9). However, we can observe a considerably lower standard error for the years of education coefficient in model (2) when compared to Table 8 models 1 through 6.

Moving on now to the manual 2SLS, as expected, the reported coefficients in models 3 thorugh 6 in Table 9 correspond exactly with those reported in Table 8 (models 1 through 4). However, the manual 2SLS does not correct for the fact that years of education (hat) originates as a predicted outcome of the first stage. Thus, the standard errors differ slightly. COnsidering how which model to prefer, OLS vs model of methods or IVREG, the Hausman's χ^2 can be used to assess which estimator is to be preferred. These are output from the $summary(IVREG_model, diagnostics = TRUE)$ in R, together with a test for weak instruments and, in case of overidentification, the Sargan-Hansen χ^2 over-identification test. To keep it short, two models are considered fro demonstrative purposes: 1) Table 8 model (3) where qob is a numeric varaible (so no overidentification), and 2) Table 8 model (5) is considered where *yob* (year of birth) was added as an instrument to demonstrate over identification. Please note that thechically, the inclusion of qob as a factor implies overidentification of the first stage; this will be ignored in this question.

Considering Table 10, the weak instruments test, which is just a partial F-test on the first stage of 2SLS, reports significant F statistics for both models (model 3: $FStatistic = 100.159$, $p < 0.01$; model 5:$FStatistic = 557.21$, $p < 0.01$), suggesting that the relevance criterion is fulfilled. Moving to the Wu-Hausman test however, the models differ. Model (3) (qob numeric model) reports and insignificant test statistic ($\chi^2 = 2.477$, $p = 0.116$), suggesting a preference for the OLS estimator. Contrarily, Model (5) reports a significant test statistic ($\chi^2 = 82.16$), suggesting that the usage of model of methods (2SLS) is preferred over OLS in this case.[9] Finally, considering the question of overidentification, this is not applicable to model (3), when considering qob as a numeric; it would, however, be relevant if we considered qob as a factor. Model (5), on the other hand, contains a second instrument, year of birth, as a demonstrative example. As can be seen in Table 10, the Sargan-Hansen χ^2 test of overidentification reports a significant test statistic ($\chi^2 = 18.84$, $p < 0.01$). Rejecting the null hypothesis implies that indepedence of the instruments of the residuals cannot be assumed. Thus, the instruments themselfes are assumed to be endogeneous themselfes and overidentification poses a problem for model (5). It may be interesting to note that if we considered qob as a factor, this test statistic would be insignificant, suggesting that the qob as a factor is exogenoeus and, thus, overidentification is no problem.

df1 df2 statistic p-value Weak instruments 1 329505 100.159 ¡2e-16 *** Wu-Hausman 1 329504 2.477 0.116 Sargan 0 NA NA NA

Diagnostic tests: df1 df2 statistic p-value Weak instruments 2 329504 557.21 ¡ 2e-16 *** Wu-Hausman 1 329504 82.16 ¡ 2e-16 *** Sargan 1 NA 18.84 1.42e-05 ***

2.6 6 –

CLeanliness; Endogeneity of independent; Relevance –¿ Cleanliness

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

Table 10: 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

5 Code

[9] Please note that I included this example on purpose

Table 11: 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

Table 12: 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.

Table 13: IV REGRESSION OUTPUT BACKUP TABLE

	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. *** p<0.01, ** p<0.05, * p<0.1.