

**UNIVERSITY OF OSLO**  
**DEPARTMENT OF ECONOMICS**

Exam: **ECON5100/9100 – Advanced Econometrics**

Date of exam: Monday, December 21, 2015      **Grades are given: January 11, 2016**

Time for exam: 09.00 a.m. – 12.00 noon

The problem set covers 5 pages (incl. cover sheet)

Resources allowed:

- Open book exam, where all written and printed resources – as well as calculator - are allowed

The grades given: Students on master's level: A-F, with A as the best and E as the weakest passing grade. F is fail. Students at ph.d. level: Pass/fail.

# Exam ECON4136, ECON5100, ECON9100 – Fall 2015

---

IMPORTANT: Always explain answers. Answers should show knowledge and understanding of the concepts taught in the course. Subquestions are weighted equally. Be to the point: We value correct answers, not long answers.

---

1. (20%) True or false? Explain your answer, if possible formally.
  - (a) “No causation without manipulation.”
  - (b) "In an experiment where treatment was randomized conditional on X you do not need to control for X to obtain a consistent estimate of the average treatment effect as long as treatment effects are the same for everyone."
  - (c) "In an experiment on a non-representative sample of individuals where treatment was randomized, you do not need to use sample weights to obtain a consistent estimate of the population average treatment effect as long as treatment effects are the same for everyone."
  
2. (50%) Ravallion et al. (JHR, 2005) study a program that provides work to poor unemployed workers on community projects that last not more than six months. They are interested how this "workfare" program affects income. They estimate an effect by comparing the observed income changes between those who leave the program (“leavers”, who are treated in period 1 and untreated in period 2) to those who do not leave (“stayers”, who are treated in both periods).
  - (a) Explain the main idea and assumption behind this estimator, and the population causal effect that it estimates under these assumptions.

There are two periods:  $t = 1, 2$  and the variable  $POST$  equals one in period 2 and is zero otherwise. Let  $P_i$  be a binary variable that equals one for initial participants and is zero otherwise,  $D_{it}$  equals one if individual  $i$  was treated in period  $t$ . Let  $L_i$  equals one for leavers and zero otherwise. Finally, let  $Y_{it}$  be income and  $X_i$  are predetermined covariates.

- (b) What OLS specification provides the estimate in (2) as a coefficient on a single variable?

Ravallion et al. (JHR, 2005) also match leavers and stayers using propensity scores (PS) derived from their observed characteristics  $X_i$ , and calculate the estimate in (a) for these groups.

- (c) Explain why you may want to do this.

- (d) Explain how you would estimate this effect using OLS, and how is this different compared to PS matching? Explain.
- (e) Explain how you would estimate this effect using inverse probability weighting (instead of matching).
- (f) Suppose your PS estimate is biased upward by 10% for all observations. Would you prefer PS matching or inverse probability weighting? Explain.

Ravallion et al. also track income changes for non-participants. They have non-participants ( $P_i = 0$ ) that are comparable to leavers ( $M_i = 1$ ) and non-participants that are comparable to stayers ( $M_i = 0$ ). Using these comparison groups they first calculate the effect in (a) and then calculate a triple-difference, namely the difference between this effect and the effect calculate using actual leavers and stayers in (a).

- (g) Explain why you may want to do this.
- (h) Explain how you would use this information and OLS to estimate the effect in (g).

The following information comes from Table 5 in Ravallion et al. and reports income in US\$:

	$D_{i2} = 1$		$P_i = 0$	
	$D_{i1} = 1$	$D_{i1} = 0$	$M_i = 0$	$M_i = 1$
$t = 1$	228.9	282.7	223.6	294.4
$t = 2$	228.4	277.3	83.0	288.8

- (i) Compute the estimates of (a) and (g).
3. (30%) Conditional on i) year of applying (gyear1), and ii) a lottery group (lotingcat\_gyear1), admission to medical school in the Netherlands is determined through a lottery. In case of a succesful lottery (res1=1, zero otherwise) applicants are admitted. People who are not admitted can reapply the following year, in principle until they are admitted.

The attached Stata output provides an estimate of an effect of completing medical school (a6551=1, zero otherwise) on whether people smoke (smoke=1, zero otherwise).

- (a) Explain the motivation behind the implemented estimation approach and specification.
- (b) Interpret and discuss the resulting estimate IV estimate.
- (c) Assume, in addition to the standard heterogenous effects IV assumptions, that there are no never takers. What is the proportion of always takers in this population of applicants?
- (d) Given the assumptions in (c), also suppose that the IV estimate is the same as the ATT, what does this imply? Discuss.

```
. sum smoke a6551 res1
```

Variable	Obs	Mean	Std. Dev.	Min	Max
smoke	10,475	.0470644	.2117868	0	1
a6551	10,475	.7030072	.4569552	0	1
res1	10,475	.5565632	.496814	0	1

```
. ivregress 2sls smoke (a6551 = res1) gyear1##lotingcat_gyear1, robust first
```

```
First-stage regressions
```

```

Number of obs   =   10,475
F( 24, 10450)   =   163.72
Prob > F        =   0.0000
R-squared       =   0.2919
Adj R-squared   =   0.2902
Root MSE       =   0.3850

```

	a6551	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
gyear1							
1989		-.0433623	.035739	-1.21	0.225	-.1134175	.0266928
1990		-.0473095	.0339488	-1.39	0.163	-.1138556	.0192366
1991		-.0408349	.0365193	-1.12	0.264	-.1124197	.0307498
1992		.0343442	.0331562	1.04	0.300	-.0306483	.0993367
1993		.0619796	.0367616	1.69	0.092	-.01008	.1340393
lotingcat_gyear1							
4		-.0492484	.0316572	-1.56	0.120	-.1113025	.0128058
5		-.0670089	.0311418	-2.15	0.031	-.1280528	-.0059649
6		-.1157563	.0300897	-3.85	0.000	-.1747377	-.0567748
gyear1##lotingcat_gyear1							
1989 4		.0781227	.0447341	1.75	0.081	-.0095647	.1658101
1989 5		.1035126	.0439624	2.35	0.019	.0173378	.1896873
1989 6		.0904545	.0425808	2.12	0.034	.006988	.173921
1990 4		.0922229	.0425566	2.17	0.030	.0088038	.1756421
1990 5		.0790831	.0425156	1.86	0.063	-.0042557	.1624218
1990 6		.1118916	.0408304	2.74	0.006	.0318562	.191927
1991 4		.0875198	.0445632	1.96	0.050	.0001675	.1748722
1991 5		.1256995	.0442349	2.84	0.004	.0389906	.2124083
1991 6		.0974533	.0428697	2.27	0.023	.0134205	.1814862
1992 4		.0366125	.0423551	0.86	0.387	-.0464115	.1196365
1992 5		.0056983	.0422542	0.13	0.893	-.077128	.0885247
1992 6		.029925	.0400774	0.75	0.455	-.0486343	.1084844
1993 4		-.0069786	.0453006	-0.15	0.878	-.0957765	.0818194
1993 5		.0005746	.0445114	0.01	0.990	-.0866763	.0878255
1993 6		.0201239	.0425038	0.47	0.636	-.0631916	.1034395
res1		.4885176	.0082952	58.89	0.000	.4722573	.5047778
_cons		.461187	.0265026	17.40	0.000	.4092369	.5131371

```
Instrumental variables (2SLS) regression
```

```
Number of obs = 10,475
```

Wald chi2(24) = 59.29  
 Prob > chi2 = 0.0001  
 R-squared = 0.0019  
 Root MSE = .21158

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
smoke						
a6551	-.0086397	.0088808	-0.97	0.331	-.0260457	.0087664
gyear1						
1989	.0347339	.0177988	1.95	0.051	-.000151	.0696189
1990	.047936	.0181253	2.64	0.008	.012411	.0834609
1991	.0326396	.0162375	2.01	0.044	.0008146	.0644646
1992	.0348193	.0158338	2.20	0.028	.0037855	.065853
1993	.0412218	.0170437	2.42	0.016	.0078167	.0746269
lotingcat_gyear1						
4	.0185372	.0104965	1.77	0.077	-.0020355	.03911
5	.018639	.0104263	1.79	0.074	-.0017961	.0390741
6	.0431817	.0114693	3.76	0.000	.0207023	.0656611
gyear1#lotingcat_gyear1						
1989 4	-.0233708	.0220295	-1.06	0.289	-.0665478	.0198061
1989 5	-.0111464	.0222226	-0.50	0.616	-.0547019	.0324092
1989 6	-.040292	.0219521	-1.84	0.066	-.0833173	.0027333
1990 4	-.0311664	.0223196	-1.40	0.163	-.0749121	.0125792
1990 5	-.0263754	.0222341	-1.19	0.236	-.0699534	.0172025
1990 6	-.0433173	.0224925	-1.93	0.054	-.0874018	.0007672
1991 4	-.0038175	.0210735	-0.18	0.856	-.0451207	.0374857
1991 5	-.0097842	.0205292	-0.48	0.634	-.0500207	.0304523
1991 6	-.0275724	.0206528	-1.34	0.182	-.0680512	.0129064
1992 4	-.0268812	.0198032	-1.36	0.175	-.0656949	.0119324
1992 5	-.0056994	.0206419	-0.28	0.782	-.0461567	.0347579
1992 6	-.0308906	.0201648	-1.53	0.126	-.0704129	.0086317
1993 4	-.0348646	.0204689	-1.70	0.089	-.074983	.0052537
1993 5	-.0214257	.020749	-1.03	0.302	-.062093	.0192416
1993 6	-.035749	.0208166	-1.72	0.086	-.0765488	.0050509
_cons	.0142721	.0102321	1.39	0.163	-.0057824	.0343267

Instrumented: a6551  
 Instruments: 1989.gyear1 1990.gyear1 1991.gyear1 1992.gyear1 1993.gyear1  
 4.lotingcat\_gyear1 5.lotingcat\_gyear1 6.lotingcat\_gyear1  
 1989.gyear1#4.lotingcat\_gyear1 1989.gyear1#5.lotingcat\_gyear1  
 1989.gyear1#6.lotingcat\_gyear1 1990.gyear1#4.lotingcat\_gyear1  
 1990.gyear1#5.lotingcat\_gyear1 1990.gyear1#6.lotingcat\_gyear1  
 1991.gyear1#4.lotingcat\_gyear1 1991.gyear1#5.lotingcat\_gyear1  
 1991.gyear1#6.lotingcat\_gyear1 1992.gyear1#4.lotingcat\_gyear1  
 1992.gyear1#5.lotingcat\_gyear1 1992.gyear1#6.lotingcat\_gyear1  
 1993.gyear1#4.lotingcat\_gyear1 1993.gyear1#5.lotingcat\_gyear1  
 1993.gyear1#6.lotingcat\_gyear1 res1