

**Suggested Answers
Problem Set 8**

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1.
 - a. $N=25, k=5, \hat{d} = 1.80, \text{lower}=0.953, \text{upper}=1.886$, since $\text{lower} < \hat{d} < \text{upper}$ the test is inconclusive
 - b. $N=60, k=9, \hat{d} = 0.23, \text{lower}=1.260, \text{upper}=1.939$, since $\hat{d} < \text{lower}$, we can reject the null that $\rho=0$
 - c. $N=45, k=2, \hat{d} = 1.40, \text{lower}=1.430, \text{upper}=1.615$, since $\hat{d} < \text{lower}$, we can reject the null that $\rho=0$

2.
 - a. False -- $\hat{\beta}_1$ is still unbiased even in the presence of autocorrelation
 - b. True -- $\text{Var}(\hat{\beta}_1)$ is too small in this situation
 - c. False – Although the OLS and the AR(1) corrected estimates are both unbiased, because we are working with finite samples, there is little chance these two estimates will produce identical results
 - d. False – Measurement error in y such as this only increases variance, it does not produce biased estimates – which means part e is TRUE
 - e. True --
 - f. True – with classical measurement error, the OLS estimated tends to be attenuated towards zero

3. The answers for this question are contained in the program titled michigan_dnd.do.

The results for models (1) – (3) are below

The means for the 2 x 2 table are as follows:

```
.
. * get means of smoked for 2 x 2 table
. by michigan after: sum smoked

-----
-> michigan = 0, after = 0

  Variable |      Obs      Mean   Std. Dev.   Min     Max
-----+-----
   smoked |   15152   .1855861   .3887851     0       1
-----

-> michigan = 0, after = 1

  Variable |      Obs      Mean   Std. Dev.   Min     Max
-----+-----
   smoked |    7304   .1856517   .388852     0       1
-----

-> michigan = 1, after = 0

  Variable |      Obs      Mean   Std. Dev.   Min     Max
-----+-----
   smoked |   53232   .1922904   .3941037     0       1
-----

-> michigan = 1, after = 1

  Variable |      Obs      Mean   Std. Dev.   Min     Max
```

```
smoked |      25988      .1786979      .3831065      0      1
```

Putting these means into the 2x2 table, we obtain a difference in difference estimate of -0.0137 or, the tax hike reduce smoking rates among pregnant women in Michigan by 1.36 percentage points

	Before (1)	After (2)	Difference (2) - (1)
Michigan (1)	0.1923	0.1787	-0.0136
Iowa (2)	0.1856	0.1857	0.0001
Difference (1) - (2)			-0.0137

Now, estimating the model within a regression, we obtain the following:

```

Source |      SS      df      MS
-----+-----
Model |  3.3128883      3  1.1042961
Residual | 15476.2314101672  .152217242
-----+-----
Total | 15479.5443101675  .152245333

Number of obs = 101676
F( 3,101672) = 7.25
Prob > F = 0.0001
R-squared = 0.0002
Adj R-squared = 0.0002
Root MSE = .39015

```

```

smoked |      Coef.      Std. Err.      t    P>|t|      [95% Conf. Interval]
-----+-----
michigan |  .0067043   .0035924     1.87   0.062   -0.0003368   .0137454
after |  .0000656   .0055575     0.01   0.991   -0.0108271   .0109583
treatment | -0.0136581  .0062931    -2.17   0.030   -0.0259925  -0.0013237
_cons |  .1855861   .0031695    58.55   0.000   .1793738   .1917983

```

d) The primary assumption of the difference in difference model is that the comparison state provides an estimate of the time path of outcomes that would have occurred in the absence of the intervention. The data has two years pre tax hike (years 1 and 2) and one year post (year 3). We can test this assumption by running a fake difference in difference model. You are to estimate a difference in difference model assuming the tax hike occurred in year 2 and delete the data for year 3. In this case, the coefficient on the “treatment” effect should be zero, which it is.

```
. reg smoked michigan after2 treatment2 if year<=2
```

```

Source |      SS      df      MS
-----+-----
Model |  3.90186034      3  1.30062011
Residual | 10554.4762 68380  .15435034
-----+-----
Total | 10558.3781 68383  .154400627

Number of obs = 68384
F( 3, 68380) = 8.43
Prob > F = 0.0000
R-squared = 0.0004
Adj R-squared = 0.0003
Root MSE = .39287

```

```

smoked |      Coef.      Std. Err.      t    P>|t|      [95% Conf. Interval]
-----+-----
michigan |  .0093967   .0050651     1.86   0.064   -0.0005309   .0193244
after2 |  -0.010017  .0063859    -1.57   0.117   -0.0225334   .0024995
treatment2 | -0.0049776  .0072374    -0.69   0.492   -0.0191628   .0092076
_cons |  .1904517   .0044507    42.79   0.000   .1817284   .1991751

```

This is easier to see in a 2 x 2 box. Using only data from year 2 and 1, we see that the both states experienced a drop in smoking of roughly the same size between year 2 and 1. From the regression estimate, we cannot reject the null that the drop is the same across the two states.

	Before (year 1)	After (year 2)	Difference (year 2) – (year 1)
Michigan (1)	0.1998	0.1848	-0.0150
Iowa (2)	0.1905	0.1805	-0.0100
Difference (1) – (2)			-0.0050

4. A program to answer this question is in the program titled `smoked_dnd`. The results for models (1) through (3) are below.

Model 1

Source	SS	df	MS	Number of obs = 1020		
Model	32.8291921	2	16.414596	F(2, 1017)	=	369.06
Residual	45.2330044	1017	.044476897	Prob > F	=	0.0000
-----				R-squared	=	0.4206
Total	78.0621965	1019	.07660667	Adj R-squared	=	0.4194
-----				Root MSE	=	.2109
packs_pc_l	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
rpcil	-.0647348	.0436796	-1.48	0.139	-.1504473	.0209777
real_tax	-.0093986	.0004151	-22.64	0.000	-.0102132	-.0085841
_cons	5.81216	.4291643	13.54	0.000	4.970011	6.654309

Model 2

```
. * add state effects
. reg packs_pc_l rpcil real_tax _Is*
```

Source	SS	df	MS	Number of obs = 1020		
Model	70.6170713	52	1.3580206	F(52, 967)	=	176.38
Residual	7.44512522	967	.007699199	Prob > F	=	0.0000
-----				R-squared	=	0.9046
Total	78.0621965	1019	.07660667	Adj R-squared	=	0.8995
-----				Root MSE	=	.08775
packs_pc_l	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
rpcil	-.7787655	.0332236	-23.44	0.000	-.8439642	-.7135668
real_tax	-.0074131	.0002477	-29.92	0.000	-.0078993	-.0069269
_Istate_2	-.3447585	.0301021	-11.45	0.000	-.4038315	-.2856855
_Istate_3	-.2408913	.0313047	-7.70	0.000	-.3023244	-.1794583
_Istate_4	-.4076549	.0293303	-13.90	0.000	-.4652132	-.3500966
delete some results						
_Istate_49	-.1535768	.0290644	-5.28	0.000	-.2106134	-.0965401
_Istate_50	-.3799918	.0310106	-12.25	0.000	-.4408476	-.319136
_Istate_51	-.2216287	.0286039	-7.75	0.000	-.2777615	-.1654958
_cons	13.107	.3355447	39.06	0.000	12.44852	13.76548

Model 3

```
. * add year effects
. reg packs_pc_l rpcil real_tax _Is* _Iy*
```

Source	SS	df	MS			
Model	73.7119499	71	1.03819648	Number of obs =	1020	
Residual	4.35024662	948	.004588868	F(71, 948) =	226.24	
Total	78.0621965	1019	.07660667	Prob > F =	0.0000	
				R-squared =	0.9443	
				Adj R-squared =	0.9401	
				Root MSE =	.06774	

packs_pc_l	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
rpcil	.2818674	.0585799	4.81	0.000	.1669061	.3968287
real_tax	-.0062409	.0002227	-28.03	0.000	-.0066779	-.0058039
_Istate_2	.0926469	.0321122	2.89	0.004	.0296277	.155666
delete some results						
_Istate_50	.1260896	.0350074	3.60	0.000	.0573885	.1947906
_Istate_51	.0543776	.0264025	2.06	0.040	.0025635	.1061916
_Iyear_1982	-.0180335	.013415	-1.34	0.179	-.04436	.008293
delte some results						
_Iyear_1999	-.3664177	.0232861	-15.74	0.000	-.412116	-.3207194
_Iyear_2000	-.373204	.0255011	-14.63	0.000	-.4232492	-.3231589
_cons	2.294338	.5966798	3.85	0.000	1.123372	3.465304

Notice that as we add more control variables, the coefficient on real_tax increases along the number line (falls in absolute value) from -0.0094, to -0.0074, -0.0062. This suggests that the model we initially estimated at the start of class (model 1) is biased for two reasons. First, the fact that the coefficient increased along the number lines when we added state effects suggests that high cigarette consuming states tend to also be low taxing states. This is not surprise – states that produce tobacco tend to not tax the product much and residents in these states smoke a lot. Not controlling for the fact that states with greater than average propensity to smoke are less likely to tax will seriously bias down the parameter estimates. Note also that because the coefficient increases along the number line when we ad in time effects, it must be the case that there is persistent negative correlation between consumption and taxes over time. Over the past 40 years, smoking in the US has fallen considerably as people have learned about the dangers of smoking. At the same time, states have found it easier to raise taxes cigarettes (it is easy to raise taxes on a product when a minority of the population consume it.). Therefore, no controlling for the fact that over time that consumption levels have declined and taxes have increases will also bias down the estimates.

Notice as well that massive increase in the R² as we add state and year effects. Most of the variation in smoking rates is between states (Utah is always lower than Nevada) than within a state over time.

In model (3), a 10 cent increase in real taxes will reduce per capita cigarette consumption by 6.2%.

5. a) Start with $\text{var}(\hat{\beta}_1) = \frac{\sigma_\varepsilon^2 \sum_{i=1}^n (z_i - \bar{z})^2}{\left[\sum_{i=1}^n (x_i - \bar{x})(z_i - \bar{z}) \right]^2}$ and place $\sum_{i=1}^n (z_i - \bar{z})^2$ in the denominator

$$\text{var}(\hat{\beta}_1) = \frac{\sigma_\varepsilon^2}{\left[\sum_{i=1}^n (x_i - \bar{x})(z_i - \bar{z}) \right]^2 \cdot \sum_{i=1}^n (z_i - \bar{z})^2}$$

Divide the numerator and denominator by $\sum_{i=1}^n (x_i - \bar{x})^2$ which produces

$$\text{var}(\hat{\beta}_1^{2SLS}) = \frac{\sigma_\varepsilon^2}{\left[\sum_{i=1}^n (x_i - \bar{x})(z_i - \bar{z}) \right]^2 \cdot \sum_{i=1}^n (z_i - \bar{z})^2} \cdot \left[\frac{1}{\sum_{i=1}^n (x_i - \bar{x})^2} \right]^2 = \frac{\frac{\sigma_\varepsilon^2}{\sum_{i=1}^n (x_i - \bar{x})^2}}{\left[\frac{\sum_{i=1}^n (x_i - \bar{x})(z_i - \bar{z})}{\sum_{i=1}^n (x_i - \bar{x})^2} \right]^2 \cdot \frac{\sum_{i=1}^n (z_i - \bar{z})^2}{\sum_{i=1}^n (x_i - \bar{x})^2}}$$

Notice that the numerator is nothing more than $\text{Var}(\hat{\beta}_1^{OLS})$ where $\text{Var}(\hat{\beta}_1^{OLS}) = \frac{\sigma_\varepsilon^2}{\sum_{i=1}^n (x_i - \bar{x})^2}$. In the

denominator, divide the numerator and denominator by $(n-1)^2$

$$\frac{\left[\frac{\sum_{i=1}^n (x_i - \bar{x})(z_i - \bar{z})}{n-1} \right]^2 / (n-1)^2}{\left(\frac{\sum_{i=1}^n (z_i - \bar{z})^2}{n-1} \right) \left(\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n-1} \right)} = \frac{\hat{\sigma}_{xy}^2}{\hat{\sigma}_z^2 \hat{\sigma}_x^2} = \left(\frac{\hat{\sigma}_{xy}}{\hat{\sigma}_z \hat{\sigma}_x} \right)^2 = \hat{\rho}_{xy}^2 \text{ so therefore}$$

$$\text{var}(\hat{\beta}_1^{2SLS}) = \frac{\text{Var}(\hat{\beta}_1^{OLS})}{\hat{\rho}_{xz}^2}$$

b) If Z does a poor job of explaining Z then $\hat{\rho}_{xz} \rightarrow 0$ and $\text{var}(\hat{\beta}_1^{2SLS})$ blows up because the denominator approaches zero.

6.a) There is room for concern that this condition is not met in this case. It is clear that BMI of siblings will be correlated. However, there is some concern that having heavier siblings may signal something about an individual's earnings capacity. Suppose that some obese people have a number of habits that lead to their obesity: lack of discipline, impulsivity, inability to sacrifice today (e.g. diet, exercise) for goals in the future. It is likely that these same traits are negatively rewarded in the job market. This is why the OLS estimates are subject to an omitted variable bias. However, suppose these traits are transmitted to children through the parents – either through genetics or nurture. If this is the case, then a sibling's obesity would contain some of the information about people from this family having these negative traits as well.

- a) We know that $p \lim(\hat{\beta}_1^{2SLS}) = \beta_1 + \frac{\sigma_{z\varepsilon}}{\sigma_{zx}}$ and from the text above, this suggests that $\sigma_{z\varepsilon} < 0$, and hence, $p \lim(\hat{\beta}_1^{2SLS})$ is biased down.

7. The program that generates these results is called twin1st.do and the log is twin1st.log

- a) 60.4% of women worked last year, average weeks worked is 23 weeks and median labor income was \$1005.
- b) The answers for part b are below. The coefficient on second is -6.8 meaning that among women with one or more kids, the presence of the second child reduces weeks worked by an average of 6.8 weeks/year.

```
. ***** part b
. * run OLS of weeks on second
. reg weeks second
```

Source	SS	df	MS			
Model	71801.5838	1	71801.5838	Number of obs =	12500	
Residual	6378669.1	12498	510.375188	F(1, 12498) =	140.68	
				Prob > F =	0.0000	
				R-squared =	0.0111	
				Adj R-squared =	0.0111	
Total	6450470.68	12499	516.078941	Root MSE =	22.591	

	weeks	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
	second	-6.813862	.5744749	-11.86	0.000	-7.939921 -5.687803
	_cons	28.98838	.531307	54.56	0.000	27.94694 30.02983

- c) In part c, the presence of a twin increases the probability of having a second child by 27.5 percentage points. Why is this coefficient not 1? At the time of the birth, the presence of the twin increases family size from 1 to 2. However, many of the women who had a twin on the 1st birth would have had a second one anyway so that is the reason the twin1st coefficient is less than 1.

Notice that in the reduced form regression (weeks worked on twin1st) produces a coefficient of -0.99. Women assigned a twin on the first birth are working 1 week fewer per ye. Notice that $-0.99/0.2746 = -3.605$ which is exactly the 2SLS estimate below.

According to the OLS model, the presence of the 2nd kid reduces work by almost 7 weeks per year. In the 2SLS model, however, this number reduces to -3.6. The OLS estimate is too large by a factor of 2 suggesting large omitted variables problems in the OLS model.

```
. ***** part c
. * run the first stage, does having
. * a twin (z) increase the kids in the home (x)?
. reg second twin1st
```

Source	SS	df	MS			
Model	234.976907	1	234.976907	Number of obs =	12500	
Residual	1311.51397	12498	.104937908	F(1, 12498) =	2239.20	
				Prob > F =	0.0000	
				R-squared =	0.1519	
				Adj R-squared =	0.1519	
Total	1546.49088	12499	.123729169	Root MSE =	.32394	

second	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
twin1st	.2746051	.0058031	47.32	0.000	.2632301	.2859801
_cons	.7253949	.0039923	181.70	0.000	.7175694	.7332204

```
.
. * run the reduced form, impact of twins (z)
. * on weeks worked (y)
. reg weeks twin1st
```

Source	SS	df	MS	Number of obs =	12500
Model	3054.30028	1	3054.30028	F(1, 12498) =	5.92
Residual	6447416.38	12498	515.875851	Prob > F =	0.0150
				R-squared =	0.0005
				Adj R-squared =	0.0004
Total	6450470.68	12499	516.078941	Root MSE =	22.713

weeks	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
twin1st	-.990038	.4068821	-2.43	0.015	-1.78759	-.1924865
_cons	23.62865	.279916	84.41	0.000	23.07997	24.17732

```
.
. * run the 2sls model (Wald estimate)
. * ivregress 2sls y (x=z)
. ivregress 2sls weeks (second=twin1st)
```

Instrumental variables (2SLS) regression	Number of obs =	12500
	Wald chi2(1) =	5.97
	Prob > chi2 =	0.0145
	R-squared =	0.0087
	Root MSE =	22.618

weeks	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
second	-3.605315	1.475498	-2.44	0.015	-6.497239	-.7133917
_cons	26.24392	1.278193	20.53	0.000	23.73871	28.74913

Instrumented: second
Instruments: twin1st

..

d) In this model, we run an OLS model similar to that in part B) but we add additional covariates. Notice that the estimated impact of havin a second kid increases in magnitude from -6.8 to -9.26, providing strong evidence that the observed characteristics of the mother are correlated with whether the mother had a second child.

```
. ***** part e
. * run OLS of weeks worked model with other covariates
. reg weeks second agem agefst black other_race educm married
```

Source	SS	df	MS	Number of obs =	12500
Model	501874.986	7	71696.4266	F(7, 12492) =	150.56
				Prob > F =	0.0000

Residual		5948595.69	12492	476.192419	R-squared	=	0.0778

Total		6450470.68	12499	516.078941	Adj R-squared	=	0.0773

					Root MSE	=	21.822

weeks		Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	

second		-9.255974	.5768304	-16.05	0.000	-10.38665	-8.125297
agem		1.000666	.0462932	21.62	0.000	.9099239	1.091407
agefst		-1.110525	.065915	-16.85	0.000	-1.239728	-.9813213
black		2.722332	.6233304	4.37	0.000	1.500509	3.944156
other_race		2.647268	1.171034	2.26	0.024	.3518603	4.942676
educm		1.321557	.0847274	15.60	0.000	1.155478	1.487636
married		-5.520823	.5492189	-10.05	0.000	-6.597377	-4.444269
_cons		11.67178	1.634199	7.14	0.000	8.4685	14.87506

e) In this problem, we estimate the model from part e) but by 2SLS using `twinst` as the instrument for `second`. Notice that the model with covariates produces a 2SLS estimate on `second` of -3.8, which is only slightly larger than the Wald estimate in part c). This means that having a twin on the 1st birth is only weakly correlated with the observed characteristics (`agem`, `agefst`, `black`, etc.).

```
. ***** part f
. * run the 2sls with additional covariates in the model
. ivregress 2sls weeks agem agefst black other_race educm married (second=twin1st)
```

```
Instrumental variables (2SLS) regression                                Number of obs =    12500
                                                                    Wald chi2(7)      =    799.03
                                                                    Prob > chi2       =    0.0000
                                                                    R-squared         =    0.0713
                                                                    Root MSE         =    21.892
```

weeks		Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	

second		-3.840711	1.388089	-2.77	0.006	-6.561314	-1.120107
agem		.893219	.052759	16.93	0.000	.7898133	.9966247
agefst		-1.00932	.0702044	-14.38	0.000	-1.146918	-.8717218
black		2.761305	.6253911	4.42	0.000	1.535561	3.987049
other_race		2.651669	1.174782	2.26	0.024	.3491376	4.9542
educm		1.338171	.0850866	15.73	0.000	1.171404	1.504938
married		-6.005684	.5624385	-10.68	0.000	-7.108044	-4.903325
_cons		8.371989	1.810752	4.62	0.000	4.822981	11.921

```
Instrumented:    second
Instruments:    agem agefst black other_race educm married twin1st
```

8. a. One would anticipate that people in most need of medical care (i.e., highest risk or mortality) would also receive the greatest amount of care or $\text{cov}(x_i, \varepsilon_i) > 0$. We know that $E[\hat{\beta}_1] = \beta_1 + \frac{\sigma_{x\varepsilon}}{\sigma_x^2}$. Since we anticipate that $\beta_1 < 0$ and $\text{cov}(x_i, \varepsilon_i) > 0$, then $E[\hat{\beta}_1] > \beta_1$.

- b) The two figures suggest that babies with slightly lower weight than 1500 grams have a lot more spent on them, which translates into better health since mortality for this group is lower.
- c) The 2SLS estimate is the reduced form divided by the 1st stage or $\hat{\beta}_1 = \hat{\pi}_1 / \hat{\theta}_1 = -0.02280 / 7670 = -2.97E-6$. this means that for every additional \$10K in spending on a low weight infant, mortality falls by $(10,000)(-2.97E-6)$ by 0.0297 or 2.97 percentage points.
- d) RDD models assume that the health of infants just above and below 1500 grams are functionally the same in the absence of treatment. Therefore, we can use the stark increase in treatment intensity right below 1500 grams to estimate the impact of spending on outcomes.
- e) This RDD model only estimates the impact of greater health care spending at 1500 grams – it does not say anything about increased spending on health care at other birth weights. RDD models have high internal validity – in most situations they have low external validity.