Sample exam.

1. This question is inspired by a study published (by Andrew Rose) in Journal of International Economics in July 2004. The study is entitled "Do WTO Members have More Liberal Trade Policy?" Suppose using cross sectional data across countries in a certain year, the following equation is estimated:

$open_i = \beta_0 + \beta_1 WTO_i + \beta_2 OECD_i + \beta_3 WTO_i \cdot OECD_i + \beta_4 population_i + u_i.$

Here i denotes country, u denotes the unobserved factors, and the variables are
open: measure of openness, i.e., (exports + imports)/gross domestic product (GDP)
WTO: binary indicator defined as 1 for World Trade Organization (WTO) members (0 otherwise)
OECD: binary indicator defined as 1 for Organization for Economic Cooperation and Development (OECD) members (0 otherwise)
population: population size.

a. Controlling for population size, which coefficient (or combination of coefficients) captures the difference in openness between WTO members and countries that are neither WTO nor OECD members?

Answer: β_1.

b. Controlling for population size, which coefficient (or combination of coefficients) captures the difference in openness between OECD members and countries that are neither WTO nor OECD members?

Answer: β_2.

c. Controlling for population size, which coefficient (or combination of coefficients) captures the difference in openness between countries belonging to both the WTO and OECD and countries that are neither WTO nor OECD members?

Answer: $\beta_1 + \beta_2 + \beta_3$.

d. In the above equation, can we add a non-WTO membership dummy defined as 1-WTO? Why or why not?

Answer: No, due to perfect collinearity or the dummy variable trap.

2. This question is inspired by a recent study published (by Kitae Sohn) in Economics & Human Biology in November 2017. The study is entitled "The Association between Height and Hypertension in Indonesia." Suppose, using cross sectional data on individuals in a certain year, the following linear probability model (LPM) is estimated by ordinary least squares (OLS):

$\text{hypertension}_i = \beta_0 + \beta_1\text{height}_i + u_i$.

Here i denotes individual, u denotes the unobserved factors, and the variables are
hypertension: binary indicator defined as 1 for people with high blood pressure (0 otherwise)
height: height in cm.

a. Are the errors in a LPM homoskedastic?

Answer: No, the errors are necessarily heteroskedastic.

b. If β_1 is estimated as -0.461, how would we interpret this coefficient estimate corresponding to height?

Answer: An increase in height by 1 cm is associated with a decrease in the probability of hypertension by 0.46.

c. Specify one advantage of estimating the above relationship between hypertension and height using a logit or probit model instead of OLS.

Answer: One advantage is that the predicted probabilities are always between 0 and 1.

d. For a logit or probit model, the marginal effect of height on the probability of hypertension is not constant across all observations. Specify two approaches of calculating the marginal effect for such models?

Answer: One approach would be to calculate the effect at the average value of height. Alternatively, we can calculate the observation-specific marginal effects and then take the average.

3. This question is inspired by a recent study published (by Kara Reynolds and John Palatucci) in Contemporary Economic Policy in February 2011. The study is entitled "Does Trade Adjustment Assistance Make a Difference?" Here, the objective is to estimate the effect of the U.S. Trade Adjustment Assistance (TAA) program on the wage of participants. The TAA program helps workers who lose their jobs due to imports with benefits such as job training.

Suppose, the treatment variable is a dummy depicting an individual's TAA participation, and the dependent variable is the worker's weekly wage after the TAA. To estimate the effect of TAA on wage, we also control for years of education, age, and industry unionization rate.

a. If we wish to employ propensity score matching to estimate the causal effect of interest, how would we estimate the propensity score? In other words, what would be the dependent and independent variables in our propensity score equation?

Answer: Typically, the propensity score is estimated from a logit or probit specification. Here, the dependent variable would be TAA participation. The independent variables are education, age, and unionization rate.

b. What is the advantage of such matching over OLS?

Answer: We do not assume the outcome equation to be linear.

c. Does matching account for the possibility that participation in the TAA program is correlated other unobserved determinants of wage such as ability or motivation?

Answer: No.

4. This question is inspired by a recent study published (by Evelina Gavrilova, Takuma Kamada, and Floris Zoutman) in Economic Journal in January 2019. The study is entitled "Is Legal Pot Crippling Mexican Drug Trafficking Organizations? The Effect of Medical Marijuana Laws on US Crime." The state-level data from the U.S. is a panel with data across all states from two years, i.e., 1995 and 2010. The following equation is estimated:

$crime_{it} = \beta_0 + \delta_0 d10_t + \beta_1 MM_{it} + \beta_2 \log(income_{it}) + u_{it}$.

Here i denotes state, t denotes year, u denotes the unobserved factors, and the variables are
crime: crime rate per 100,000 inhabitants
d10: binary indicator defined as 1 for 2010 (0 otherwise)
MM: binary indicator defined as 1 for states that decriminalize production and consumption of (medical) marijuana (0 otherwise); note that no state decriminalized in 1995 but some did by 2010
income: median income.

a. Suppose the above regression is estimated by OLS, and the corresponding estimate of β_1 is 174.44. How would you interpret this coefficient estimate corresponding to MM?

Answer: Decriminalizing production and consumption of (medical) marijuana in a state is associated with an increase in crime rate of about 174.44 per 100,000 inhabitants.

b. Next, suppose $u_{it} = a_i + v_{it}$, such that MM_{it} and a_i are correlated. In other words, a_i is a time-invariant state characteristic that affects crime and is also correlated with MM. For example, think of inland states versus those bordering Mexico, or presence of local gangs. In such a scenario, what is a drawback of an OLS approach?

Answer: In this case, our OLS estimator is biased due to the correlation between MM_{it} and a_i.

c. Next, suppose $u_{it} = a_i + v_{it}$, such that MM_{it} and a_i are correlated. In other words, a_i is a time-invariant state characteristic that affects crime and is also correlated with MM. For example, think of inland states versus those bordering Mexico, or presence of local gangs. In such a scenario, given the drawback of an OLS approach, what estimation strategy would you pursue to control such for time-invariant state characteristics?

Answer: First-differencing.

d. Next, suppose $u_{it} = a_i + v_{it}$, such that MM_{it} and a_i are correlated. In other words, a_i is a time-invariant state characteristic that affects crime and is also correlated with MM. For example, think of inland states versus those bordering Mexico, or presence of local gangs. In such a scenario, say we use an estimation strategy to control such for time-invariant state characteristics. However, suppose v_{it} includes some measure of drug violence such that v_{it} is uncorrelated with MM_{it}, but v_{it-1} (i.e., past drug violence) is correlated with MM_{it}. In this case, would your strategy to control such for the time-invariant state characteristics be valid? Why or why not?

Answer: No. First-differencing relies on the assumption of strict exogeneity which is violated in this case.

5. Suppose the relationship between state-level pollution and manufacturing output is given by:

$pollution_i = \beta_0 + \beta_1 output_i + u_i$

where i: state
pollution: measure of air pollution
output: manufacturing output
u: unobserved characteristics such as environmental regulation.

Say, output and u are correlated such that the OLS estimator is biased and inconsistent.

a. If the minimum wage in a state (denoted by z) is regarded as an instrumental variable (IV) for output, what properties must it satisfy in terms of its correlation with output and u?

Answer: z must be correlated with output but uncorrelated with u.

6. Suppose we are interested in examining the effect of attending a Catholic high school on the probability of attending college. The relationship between the two variables is given by:

$college_i = \beta_0 + \beta_1 CathHS_i + other\ factors_i + u_i$

where i: student
CathHS: binary variable equal to 1 if a student attends a Catholic high school
college: binary variable equal to 1 if a student attends college within two years of graduating from high school
other factors: include gender, race, family income, and parental education
u: unobserved characteristics such as ability and location.

Say, CathHS and u are correlated such that the OLS estimator is biased and inconsistent.

a. Say CathRel is a binary variable equal to one if a student is Catholic. Discuss the two requirements needed for CathRel to be a valid instrument for CathHS. Which of these can be tested?

Answer: CathRel must be correlated with CathHS after controlling for the variables included in other factors. However, it must be uncorrelated with u. We can only test the first assumption.

b. In this setup, what would the problem of weak instruments be?

Answer: The issue would be low correlation between CathHS and CathRel after controlling for the variables included in other factors.