Labor Economics Field Exam

Summer 2022

There are three sections, one for each required course. Each has multiple subparts. You must answer all sections.

ECON 244

You are running a randomized trial evaluating a new medical treatment. You recruit a large random sample of the population for the trial, but not all recruited subjects agree to participate. Let E_i denote an indicator variable equal to one if subject i agrees to participate in the experiment and zero otherwise. Subjects who refuse to participate in the experiment cannot receive the treatment. Within the experimental sample with $E_i = 1$, you assign subjects to either receive the treatment ($T_i = 1$) or to the control group ($T_i = 0$). At the end of the trial you observe whether each experimental subject got sick ($Y_i = 1$) or remained healthy ($Y_i = 0$).

A. Let $Y_i(1) \in \{0, 1\}$ denote subject i's potential health outcome if assigned to the treatment, and let $Y_i(0)$ denote i's potential outcome if assigned to the control group. Suppose you randomly assign experiental subjects to treatment or control, so that $(Y_i(1), Y_i(0)) \perp\!\!\!\perp T_i | E_i = 1$. Show that you can use the experiment to identify the average treatment effect in the experimental population, $\delta_E \equiv E[Y_i(1) - Y_i(0)|E_i = 1]$.

B. Suppose that a fraction p of the population agrees to participate in the trial. Show how to use the experiment to compute bounds for the population average treatment effect, $\delta_{ATE} \equiv E[Y_i(1) - Y_i(0)]$.

C. You observe a binary covariate $X_i \in \{0, 1\}$ for all recruited subjects, including those that refuse to participate. Let $p(x) = Pr[E_i = 1|X_i = x]$ denote the share of subjects that agree to participate for each value of x. Assume $p(x) > 0$ $\forall x$.

(i) Consider the condition:

$$(Y_i(1), Y_i(0)) \perp\!\!\!\perp E_i | X_i = x, \ x \in \{0, 1\}.$$

Explain in words what this condition means. Why might it be violated?

(ii) Suppose the condition in part C(i) holds. Show that you can use the experiment to identify δ_{ATE}.

[You can ignore the covariate X_i for parts D-F below.]

D. Suppose the treatment protocol asks treated subjects to show up to a medical facility for several doses. Not all treated subjects show up for all of the recommended doses. Let C_i denote an indicator equal to one if subject i fully complied with the treatment by showing up for all recommended doses. Let $C_i(1)$ denote i's potential value of this variable if assigned to treatment, and $C_i(0)$ denote i's value if assigned to control. Assume that subjects assigned to control cannot receive any doses, so that $C_i(0) = 0$ $\forall i$.

(i) Consider the condition

$$[C_i(1) = 0] \implies [Y_i(1) = Y_i(0)] \ \forall i.$$

Explain in words what this condition means. Why might it be violated?

(ii) Suppose the condition in part D(i) holds. Show that you can use the experiment to identify the parameter $\delta_{CE} \equiv E[Y_i(1) - Y_i(0)|C_i(1) = 1, E_i = 1]$. Provide an interpretation for this parameter.

E. Now suppose you are able to run an additional trial in the non-experimental population (those with $E_i = 0$). You randomize treatment assignment T_i in this population, and observe compliance C_i. However, you are not able to observe health status Y_i in this second experiment.

(i) Consider the condition:

$$(Y_i(1), Y_i(0)) \perp\!\!\!\perp E_i | C_i(1).$$

Explain in words what this condition means. Why might it be violated?

(ii) Suppose the conditions in part D(i) and E(i) hold. Show that you can identify δ_{ATE}.

F. After the trial is complete, a policymaker must decide whether to make the treatment available to all individuals in the population. Which of the parameters above (δ_E, δ_{ATE}, or δ_{CE}) is likely to be most useful for making this decision? Discuss implications of your answer for target parameters in program evaluations.

ECON 250A

Minimum wages and monopsony

1. Suppose that a fast food firm produces hamburgers from labor via the production function $F(l)$ where $F'(l) > 0$ and $F''(l) < 0$ for $l \in [0, \infty)$. The firm is a local monopsonist, facing a labor supply curve $L(w)$ of homogenous workers exhibiting $L'(w) > 0$ for offered wages $w \in [0, \infty)$.

a) Derive an expression for the firm's cost function $C(y)$ giving the minimal cost of producing y hamburgers. Your answer should make use of the inverse functions $F^{-1}(y)$ and $L^{-1}(l)$.

b) Derive the firm's marginal cost function $MC(y) = \frac{d}{dy}C(y)$. (Hint: recall that the derivative of an inverse function $h^{-1}(x)$ can be written $\frac{dh^{-1}(x)}{dx} = \frac{1}{h'(h^{-1}(x))}$.)

c) Suppose the price the firm is able to charge for its hamburgers is given by $P(y) = py^{-1/\varepsilon}$ where $\varepsilon > 1$ is the local elasticity of hamburger demand. Derive the marginal revenue $MR(y)$ of the y'th hamburger produced.

d) Suppose the firm had been producing hamburgers optimally at level $\underline{y}$ obeying $MR(\underline{y}) = MC(\underline{y})$ when a benevolent Oracle announces a "just binding" minimum wage $\underline{w} = L^{-1}\left(F^{-1}(\underline{y})\right)$. Will the firm produce more or fewer hamburgers? Explain your answer. (Hint: how does a binding minimum wage change the marginal cost of producing an extra hamburger?)

e) What should happen to the price of hamburgers when the minimum wage is introduced?

f) How do your predictions in parts d) and e) accord with the empirical evidence?

g) Bonus: Suppose the oracle hikes the already binding minimum wage $\underline{w}$ by a small amount. What is the passthrough elasticity $\frac{d \ln P(y)}{d \ln \underline{w}}$? Does the sign of this elasticity accord with the empirical evidence?

ECON 250B

Borjas (2003) and Ottaviano and Peri (2012) both study the effect of immigration on wages, using panel data on wages and quantities of native and immigrant workers of different education and experience levels over time. They use approximately the same data sources, relying primarily on Decennial Census data, and similar modeling strategies.

Each paper models output Y as a CES function of capital and labor, $Y = f(K, L)$, where L is a CES aggregate of labor of different types. The basic strategies are summarized below to refresh your memory; you should also have access to hard copies of the papers themselves to refer to if you like. Despite the two papers' strong similarities, they come to quite different conclusions.

1. Summarize in a few sentences the key empirical results from each paper.
2. Describe how the different modeling choices that the two papers make lead them to such different results.
3. Suppose you had aggregate data similar to what is used in these papers, with observations on labor supply and wages at the education-experience-nativity-time level, L_{ijbt} and $\ln w_{ijbt}$ (as well as higher-level aggregates of these). Describe an analysis that you could conduct with these data that would help you to adjudicate between the different assumptions that the authors make about the role of immigrant workers in the labor market.
4. Each paper uses four education groups – less than high school, high school graduates, some college, and college graduates. Consider the alternative of using just two groups, high school or less and some college or more. What are the advantages and drawbacks of this approach? What kind of evidence would lead a researcher using the Borjas and/or Ottaviano-Peri strategies to favor or disfavor this approach?
5. A separate literature studies "skill-biased technical change," the idea that technological change in recent decades has shifted the production function in a way that reduces the productivity of lower-skilled (i.e., less educated) labor and increases the productivity of higher-skilled (more educated) labor. What, if anything, would the existence of SBTC imply for the empirical strategies used by Borjas and Ottaviano and Peri?

This is the end of the question. What follows is a brief overview of the basic setups of the two papers, to refresh your memory. I modify notation slightly to minimize differences between them. You can refer to the papers themselves for the original notation.

In Borjas (2003), aggregate labor supply at time t is $L_t = \left[\sum_i \theta_{it} L_{it}^{\frac{\sigma_E - 1}{\sigma_E}}\right]^{\frac{\sigma_E}{\sigma_E - 1}}$, where $L_{it} = \left[\sum_j \alpha_{ij} L_{ijt}^{\frac{\sigma_X - 1}{\sigma_X}}\right]^{\frac{\sigma_X}{\sigma_X - 1}}$. Here, L_{ijt} is the number of workers in education group i and experience group j at time t, and L_{it} is a composite representing the effective supply of education i labor at time t. The parameter σ_E is the elasticity of substitution between education groups, while σ_X is the elasticity of substitution across experience groups within an education group. Immigration affects wages by changing the supply of labor within education-experience-time cells, L_{ijt}.

Borjas shows that the marginal productivity condition implies the following wage equation:

$$\log w_{ijt} = \delta_t + \delta_{it} + \delta_{ij} + \beta \log L_{ijt},$$

where $\beta = -1/\sigma_X$ and $\delta_{ij} = \log \alpha_{ij}$. Thus, the substitution elasticity σ_X and the weights α_{ij} can be estimated from a regression of log wages in an education-experience-time cell on the number of workers in the cell, with education-by-time and education-by-experience fixed effects. The number of workers in the cell is the sum of native and immigrant workers, $L_{ijt} = N_{ijt} + M_{ijt}$. Because native labor supply may be endogenous, Borjas instruments for L_{ijt} with M_{ijt}.

Once he estimates this regression, Borjas uses the parameters α_{it} and σ_X to construct the aggregate L_{it}, which he shows is related to average log wages in education-time cells by

$$\log w_{it} = \delta_t + \log \theta_{it} - (1/\sigma_E) \log L_{it}.$$

He imposes the restriction that θ_{it} follows a linear time trend for each education group, $\theta_{it} = \theta_i^0 + \theta_i^1 t$, and identifies σ_E from a regression of $\log w_{it}$ on $\log L_{it}$ with education group and time fixed effects and education-specific trends. Again, he instruments $\log L_{it}$ with an analogous measure constructed just from counts of the number of immigrants in each $i-j-t$ cell, $\log M_{it}$, where

$$M_{it} \equiv \left[\alpha_{ij} M_{ijt}^{\frac{\sigma_X - 1}{\sigma_X}} \right]^{\frac{\sigma_X}{\sigma_X - 1}}.$$

In Ottaviano and Peri (2012), the labor supply aggregate is also a nested CES, though with differences in the details. They consider several specifications, but in their "Model A," there are three layers: Birthplace (native or migrant) is nested within experience category, which in turn is nested within education groups. The labor supply aggregate is

$$L_t = \left[\sum_i \theta_i L_{it}^{\frac{\sigma_E - 1}{\sigma_E}} \right]^{\frac{\sigma_E}{\sigma_E - 1}},$$

where

$$L_{it} = \left[\sum \theta_{ij} L_{ijt}^{\frac{\sigma_X - 1}{\sigma_X}} \right]^{\frac{\sigma_X}{\sigma_X - 1}}$$

and

$$L_{ijt} = \left[\sum \theta_{ijb} L_{ijbt}^{\frac{\sigma_b - 1}{\sigma_b}} \right]^{\frac{\sigma_b}{\sigma_b - 1}}.$$

As before, i indexes education, j indexes experience, and t indexes time; here, we also introduce b indexing birthplace (native or abroad). The elasticity of substitution between workers of different education levels is σ_E, the substitution elasticity between workers of different experience at the same education level is σ_X, and the substitution elasticity between workers of different nativity within education-experience groups is σ_b.

Ottaviano and Peri show that this setup implies a simple relationship between wages of workers of different nativity within education-experience cells:

$$\ln\left(\frac{w_{ijbt}}{w_{ijb't}}\right) = \ln \frac{\theta_{ijb}}{\theta_{ijb'}} - \frac{1}{\sigma_N} \ln\left(\frac{L_{ijbt}}{L_{ijb't}}\right).$$

The elasticity σ_N is thus identified from panel data on native and immigrant wages and quantities over time within education-experience cells, by regressing the native-immigrant wage difference on the native-immigrant supply difference with education-experience fixed effects. As in Borjas, these estimates are used to construct the higher-level aggregate L_{ijt}. Next, a regression of $\ln w_{ijt}$ on $\ln L_{ijt}$ with time and education-experience fixed effects identifies σ_X. This is again used to construct the next-higher aggregate L_{it}, and they again regress $\ln w_{it}$ on $\ln L_{it}$, this time with time and education fixed effects, to identify σ_E.