Problem Set 6

MGMT 737

1. **Event Study** We consider an event study approach. We will use data from Sun and Abraham (2021)'s application, which replicates results from Dobkin et al. (2020)'s results using the HRS data (which is publicly available). Variables: `hhidpn` household identifier – this is the identifier for an individual in the panel; `wave` time identifier (wave of survey) – this is the time index of the survey; `wave_hosp` time of event – time when the individual is hospitalized; and `oop_spend` Out-of-pocket spending.

   (a) We will be following Sun and Abraham's notation for describing this setup. Denote the initial time period of treatment for a unit as E_i. What variable corresponds to E_i in our dataset? Construct a variable $D_{it} = 1(E_i <= t)$ which is equal to one when an individual is treated. What share of individuals are treated in period 7,8,9,10?

   (b) Estimate the traditional static two-way fixed effects estimation for this setup:

   $$Y_{it} = \alpha_i + \lambda_t + D_{it}\beta + \epsilon_{it} \tag{1}$$

   where Y_{it} is `oop_spend`, α_i is a unit fixed effect and λ_t is a time fixed effect. Report the estimate for β and its standard error (adjust for appropriate inference in the panel setting).

   (c) Now, consider the estimation group by group. Denote our control group as the last group ever treated. For each other treated wave, estimate the treatment effect relative to this group, excluding the last period of data. Report the coefficients and standard errors for each of these waves. How do these estimates compare to your last result? For Wave 8 cohort, what is the relative comparison period for the diff-in-diff? In other words, the diff across units is Cohort Wave 8 vs. Cohort Wave 11. What is the diff across time comparing?

   (d) Now thing back to the traditional static equation – what is the relative comparison period for this diff-in-diff?

   (e) We now consider the dyanamic versions of Equation 1. Denote $D^l_{it} = 1(t - E_i = l)$

   $$Y_{it} = \alpha_i + \lambda_t + \sum_{l \in -3,-2} D^l_{it}\beta_l + \sum_{l \in 0,1,2,3} D^l_{it}\beta_l + \epsilon_{it}. \tag{2}$$

   Report the β coefficients and their standard errors.

   (f) Now, repeat this exercise, but consider the estimation group-by-group again. Focusing just on the Cohort Wave 8 vs. Cohort Wave 11 comparison, how would you run the above specification? What coefficients are you able to estimate? Report these estimates. Now repeat and estimate β_0 for each of the groups. How do these estimates compare to your estimates from Equation 2?

   (g) Now focus on the estimate for β_{-2} from Equation 2. This is traditionally the pre-trend test. Sun and Abraham show that under the standard diff-in-diff assumptions, the β_{-2} coefficient in Equation 2 specification, this coefficient is the weighted combination of multiple treatments in other periods. Denote $CATT_{e,l}$ as the average treatment effect l periods from the initial treatment for the cohort of units first treated at time e. Then, Sun and Abraham show that

   $$\beta_{-2} = \sum_{e=8}^{11} \omega^{-2}_{e,-2} CATT_{e,-2} + \sum_{l=-3,0,1,2,3} \sum_{e=8}^{11} \omega^{-2}_{e,l} CATT_{e,l} + \sum_{l' \in \{-4,-1\}} \sum_{e=8}^{11} \omega^{-2}_{e,l'} CATT_{e,l'}, \tag{3}$$

   where the ω are weights that we can calculate. We can estimate these by replacing Y_{it} in Equation 2 with $D^l_{i,t} 1(E_i = e)$ as the outcome variable, and reporting the coefficient on D^{-2}_{it}. Do so for each l and e. Your results should match Figure 2 in Sun and Abraham. How does this affect your interpretation of the pre-trend test?

(h) Finally, we estimate Sun and Abraham's alternative estimator, which avoids the contamination bias. This approach *pools* our cohort-by-cohort comparison from before. First, we estimate

$$Y_{it} = \alpha_i + \lambda_t + \sum_{e=8,9,10} \sum_{l=-3, l\neq -1}^{l=3} 1(E_i = e) \times D_{it}^{l} \delta_{e,l} + \epsilon_{it}, \tag{4}$$

where we exclude the last time period and treat the Cohort Wave 11 as our control group. Take the $\delta_{e,l}$ estimates, and report $\delta_{e,0}$ for all 3 groups. The final estimate μ_0 weights each of these δ by the cohort sample weight $\pi_e = Pr(E_i = e|l = 0)$. Report this estimate of μ_0.

2. **Synthetic Control:** We now implement the synthetic methods approach. In Stata, you should use the `sdid` package (https://github.com/Daniel-Pailanir/sdid) and in R use the `synthdid` package (https://synth-inference.github.io/synthdid/).

   (a) First, we will replicate the main **synthetic control** effect of California's Prop 99 on cigarette consumption. Setup the data following the vignette for the package. Report the treatment effect for the synthetic control. (note, this is not the main `synthdid` estimator).

   (b) Now, estimate the effect using the `synthdid` estimator. Report the treatment effect and compare to the synthetic control effect.

   (c) Take a look at the weights for the synthetic control. What variables are most important in the synthetic control? How do these weights compare to the weights in the synthetic did estimator? (In R, this is done by looking at the summary command for the estimate)

   (d) Now, let's use a new package from Cattaneo et al. https://nppackages.github.io/scpi to estimate the effect of the California Prop 99. You can find an example of the setup here: https://github.com/nppackages/scpi/blob/main/R/scpi_illustration.R. Implement the simplex version of SC. (Hint: the estimate returned by the function has a value 'est.results' that includes the year-by-year synthetic values 'Y.post.fit'. These are the synthetic california values. Contrast these with the actual values of california in the post period, and take the overall mean over the period). Contrast this with the original synthetic control estimate from synthdid (they should be close but likely not identical).

   (e) Now, estimate the prediction intervals from Cattaneo et al. (see the documentation) for discussion. Just use the defaults for the prediction intervals. Report the synthetic value estimate and left and right bound for synthtic california in 2000, and compare whether the true value is in that interval.

   (f) Finally, consider a placebo test. Pretend the treatment was in 1985, and rerun the estimation procedure. Prior to 1989, is the synthetic California significantly different from the actual California? (you can plot this using 'sc_plot')

   (g) Report the estimate and left and right bounds of synthetic california in 2000 in this version.

   (h) If you are feeling ambitious (not required), try playing around with other robustness results and see if you can account for the pre-trend differences.