ECON-810: Problem Set 2 Solutions

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Part 1: Data

The data assignment this week has two parts. One part will use our PSID dataset from last week the other part will require you to simulate data.

Earnings gains while employed

In this section, we are going to produce a moment from the PSID earnings data that we will compare to the estimates from the model in Section 2. Using the PSID data, individuals who have been working full time in two consecutive years (easy way to do this, set a lower bound on annual hours that aligns with working full-time for a full year). What is the average change in earnings for these individuals?

Answer: We removed from the PSID data the SEO oversample, our subsample is from 1970 to 2015 and our lower bound on annual hours worked is 2,000 hours.[1] The average change in earnings in our subsample is \$2,127.17, which represents an average increase of 8.7377%. For more details, see Part 1 in Appendix I: Data.

Earnings gains while employed

In this section, you will simulate data for a sample of "job losers" and job stayers. Then using the simulated data, you will test that you can recover the parameters that govern the simulation using the distributed lag framework from class. Try the following:

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[1] 2,000 hours a year (full-time job) = 8 hours a day × 5 days a week × 52 weeks in a year − 2 weeks of vacations.

- **Step 1:** Simulate data on 500 job losers and 500 job stayers for 11 years. In year 1, suppose all individuals make $30,000 plus some random (mean zero) noise. In years 2-5 (the pre- layoff years), suppose all individuals earnings increase by $1000 + random noise. For the job losers sample suppose in year 6 their earnings decline by 9,000 plus noise, and then resume increasing by 1000 per year (plus noise) until year 11. For the job stayers sample suppose in year 6 through 11 they continue to have an average increase in earnings of 1000 (plus mean zero noise).

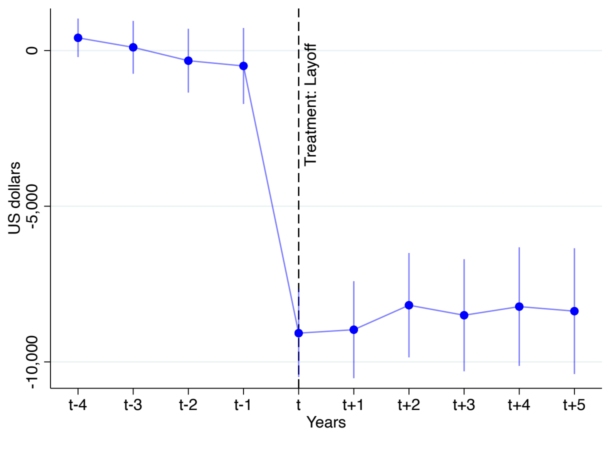
- **Step 2:** Using the simulated data from step 1, estimate the distributed lag framework from class,

$$Y_{i,t} = \alpha_i + \gamma_t + \sum_{k=-4}^{5} \beta_k D_{i,k} + \epsilon_{i,t},$$

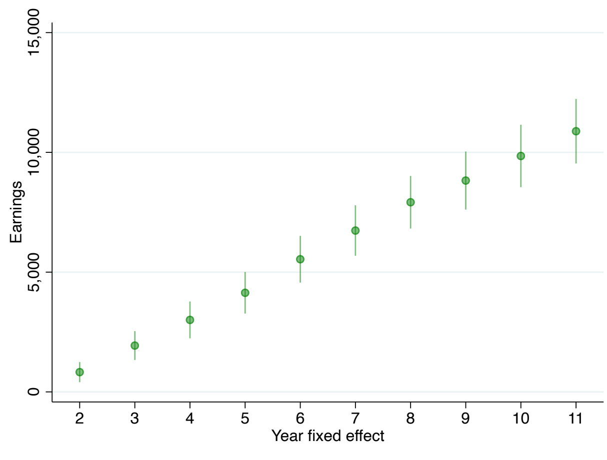
  where α_i is an individual fixed effect, γ_t are year fixed effects, $D_{i,k}$ are dummy variables denoted when an individual i is k years from layoff.

- To complete the data assignment report the coefficient estimates from estimating the distributed lag framework. What are the values of β_k and γ_t? What do you think they should be equal to?

Answer: Once we have simulated the data (see Part 2 in Appendix I: Data) we estimate the distributed lag framework. The results of the estimates are presented in Figure 2. In particular, Figure 1a presents the estimates for β_k and Figure 1b presents the estimates for the time fixed effects γ_t. As in Davis and Von Wachter (2011), we find that displacement causes large and persistent decline in earnings (even after 5 years of the layoff, earning do not recover).



(a) $\hat{\beta}_k$



(b) $\hat{\gamma}_t$

Figure 1: Estimated coefficients

Given our estimates, the present discounted value of being displaced in year 6 using a real interest rate of $r = 4\%$ is given by

$$PDV_{y=6} = \sum_{k=0}^{5} \frac{\hat{\beta}_k}{(1+0.04)^k} = -\$54,619.48.$$

Part 2: Model

Consider a simplified life-cycle version of the model in Ljungqvist and Sargent (1998). Suppose workers have linear utility (risk neutral) and live for T periods. To find jobs, workers exert search intensity s at utility cost $c(s)$. Given that effort, $\pi(s)$ is the probability of receiving a job offer. Job offers are drawn from stationary distribution $F(w)$. When employed, suppose that each period there is a probability δ of being laid off. Let h denote human capital, and take home pay will be wh. When unemployed, workers receive a transfer b, which is common to all workers.

Suppose that human capital lies on a grid $h \in \{\underline{h}, \underline{h}+\Delta, ..., \bar{h}\}$, and following the human capital process in Jarosch (2021). If unemployed, human capital falls by Δ with probability ψ_u. When employed, human capital increases by Δ with probability ψ_e.

The value function for the unemployed is given by,

$$U_t(h) = \max_s b - c(s) + \beta \mathbb{E}_{h'|h,U}\left[\pi(s)\int_w \max\left\{W_{t+1}(w,h',U(h'))\right\} dF(w) + (1-\pi(s))U_{t+1}(h')\right] \ \forall t \leq T$$
$$U_{T+1}(h) = 0,$$

subject to the law of motion for human capital among the unemployed. The value function for the employed is given by,

$$W_t(w,h) = wh + \beta \mathbb{E}_{h'|h,W}\left[(1-\delta)W_{t+1}(w,h') + \delta U_{t+1}(h')\right] \ \forall t \leq T$$
$$W_{T+1}(w,h) = 0.$$

Assignment

- Solve the model with VFI and simulate a mass of agents.
  - In the VFI there are two policy functions to store: (1) search policy function and (2) reservation wage by human capital. Each policy function is also a function of age.

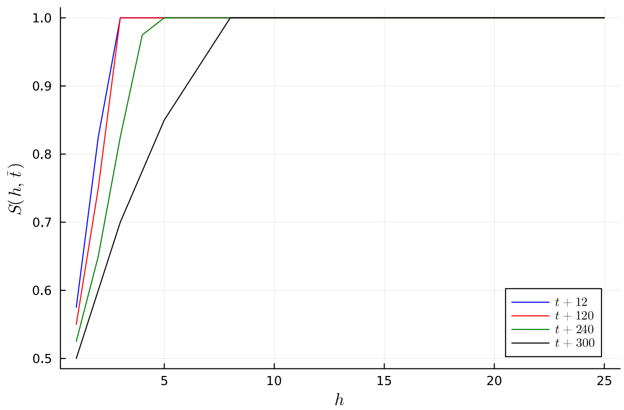
  Answer: See attached code to see value function iteration and simulation using the policy functions.

- Plot the search policy function and reservation wage as function of h for a few selected ages.

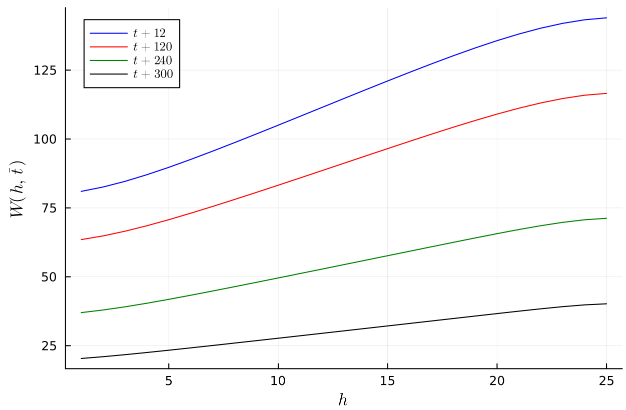
  Answer: Figure 2a displays the search policy function while Figure 2b presents the reservation wage policy function. The reservation wage policy function is increasing in human capital and, also, the policy function is shifted upwards for older agents. According to our results, as the agents gets older they tend to search less even for larger human capital levels.

- In the simulated data, plot the distribution of human capital among the employed and unemployed. Do the distribution look like you would expect?

  Answer: Figure 3 displays the distribution of human capital among employed and unemployed agents in the simulated data. As can be seen, there is more human capital accumulation for employed agents. This is consistent with the assumption presented in Jarosch (2021) that households when unemployed lose a fraction of their human capital with probability ψ_u.



(a) Search



(b) Reservation wage

Figure 2: Policy functions

Figure 3: Human capital distribution by status

- In the simulated data, what is the average gain in earnings for individuals who are working for two consecutive years (i.e., 24 periods without a δ shock)? How does this estimate compare to your estimate from the PSID data in Section 1? How does this estimate vary as you increase/decrease the parameter ψ_e.

  Answer: From the simulated data, we get that the average gain in earnings for individuals who are working for two consecutive years is 0.0073 (units) which represents an average increase of earnings of 1.5914%. Increasing ψ_e to 0.25 implies an average increase of earnings of 1.7601%. Given the subsample that we use from the PSID, we get an average increase of earnings of 8.7377%.

- In the simulated data, plot the average path of earnings from 6 months before to 2 years after an unemployment spells (i.e., a δ shock in your model). What is the percent decline in earnings after 2-years? How does this compare to the data reported in Davis and Von Wachter (2011) or Jarosch (2021)? What happens if you increase/decrease ψ_u.

  Answer: Figure 4 presents the average path of earnings from 6 months before to 2 years after an unemployment spells. The percentage decline in earnings after 2-years is -60.53%.

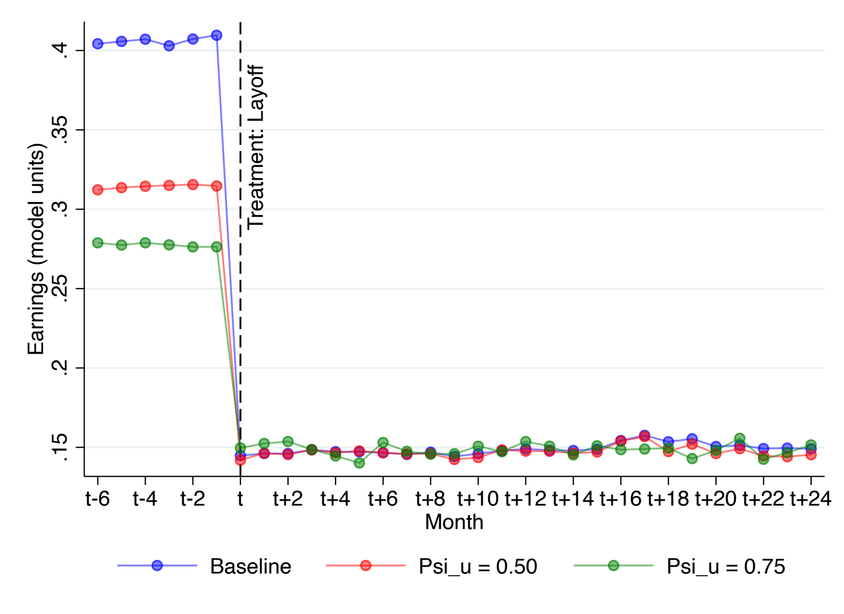


Figure 4: Effect of δ shock

Qualitatively, our results are comparable to those presented in Davis and Von Wachter (2011) and Jarosch (2021) given that, even after two years of the layoff, agents do not recover their pre-shock earnings level. Quantitatively, our results are worse given the size and duration of the contraction in earnings. As we increase the probability of decreasing human capital ψ_u, we find that average earnings before the unemployment shock is smaller and the average effect of the treatment is also smaller as ψ_u increases.

References

S. J. Davis and T. M. Von Wachter. Recessions and the Cost of Job Loss. Technical report, National Bureau of Economic Research, 2011.

G. Jarosch. Searching for Job Security and the Consequences of Job Loss. Technical report, National Bureau of Economic Research, 2021.

L. Ljungqvist and T. J. Sargent. The European Unemployment Dilemma. *Journal of Political Economy*, 106(3):514–550, 1998.

Appendix I: Data

```
/// Econ 810: Advanced Macroeconomic Theory
/// Professor: Carter Braxton
/// Problem Set 2: Earnings and job loss
/// Authors: Fernando de Lima Lopes, Stefano Lord-Medrano, Yeonggyu Yun
/// Date: 02/02/2023

////////////////////////////////////////////////////////////////////////////////
* Housekeeping
* Clear workspace
clear all
```

```
* Set directory
cd "/Users/smlm/Desktop/Datasets - Metrics/PSID data"
use pequiv_long.dta

////////////////////////////////////////////////////////////////////////////////
* Part 1: Earnings gains while employed
* Define panel
xtset x11101LL year, yearly
* Drop SEO oversample (see page 372 of Codebook for the Cross-National
* Equivalent File)
drop if x11104 == 12
* Difference in years
by x11101LL: gen dif_year = year - year[_n-1]
* Hours worked
keep if e11101 >= 2000
* Consecutive years
replace dif_year = 0 if missing(dif_year)
keep if dif_year<=1
* Generate difference in earnings
gen dif_earnings = D1.i11110
summ dif_earnings

////////////////////////////////////////////////////////////////////////////////
* Part 2: Simulation
clear
set obs 1000
gen id = _n
expand 11
bysort id: gen year = _n
xtset id year
gen e = rnormal(0,5000) if year == 1
gen y = .
replace y = 30000+e
gen losers=0
replace losers = 1 if id <= 500
gen u = rnormal(0,5000) if year >= 2
gen loss = 0
bysort id (year): replace loss=-9000 if _n == 6 & id <= 500

gen increment=0
foreach t of num 2/11 {
  bysort id (year): replace increment = 1000 + u + loss
}

gen earnings = y
foreach i of num 2/11 {
  bysort id (year): replace earnings= earnings[`i'-1] + increment[`i'] if _n ==
    `i'
}

drop y e u increment losers loss
////////////////////////////////////////////////////////////////////////////////
* Part 3: Distributed lag regression
by id: gen minus_4 = 0
by id: replace minus_4 = 1 if year - 6 == -4 & id <=500
by id: gen minus_3 = 0
by id: replace minus_3 = 1 if year - 6 == -3 & id <=500
by id: gen minus_2 = 0
by id: replace minus_2 = 1 if year - 6 == -2 & id <=500
```

```
by id: gen minus_1 = 0
by id: replace minus_1 = 1 if year - 6 == -1 & id <=500
by id: gen minus_0 = 0
by id: replace minus_0 = 1 if year - 6 == 0 & id <=500
by id: gen plus_1 = 0
by id: replace plus_1 = 1 if year - 6 == 1 & id <=500
by id: gen plus_2 = 0
by id: replace plus_2 = 1 if year - 6 == 2 & id <=500
by id: gen plus_3 = 0
by id: replace plus_3 = 1 if year - 6 == 3 & id <=500
by id: gen plus_4 = 0
by id: replace plus_4 = 1 if year - 6 == 4 & id <=500
by id: gen plus_5 = 0
by id: replace plus_5 = 1 if year - 6 == 5 & id <=500

xtreg earnings i.year minus_4 minus_3 minus_2 minus_1 minus_0 plus_1 plus_2 plus_3 plus_4 plus_5, fe vce(robust)
coefplot, vertical keep(minus_4 minus_3 minus_2 minus_1 minus_0 plus_1 plus_2 plus_3 plus_4 plus_5) nolabel recast(connected)
```

Listing 1: Data part (Stata)