

## Structural Econometrics

### Optimal Stopping-Model of Schooling

Background: *Belzil and Hansen (2002, Econometrica)* and *Belzil and Hansen (2007, Journal of Econometrics)*

- Model Structure:  $T$  periods to allocate (Finite Horizon) between two activities: work (full-time) vs education (with a maximum for schooling)
- Every individual starts in school and eventually works (limit to schooling)
- Assume to intermediate state (like no school-no work)

- Utility of attending school,  $U_{it}^s(.)$  :

$$\begin{aligned} U_{it}^s(.) &= X_i' \delta + \psi(S_{it}) + v_i^\xi + \varepsilon_{it}^\xi \\ &= \bar{U}_{it}^s(.) + \varepsilon_{it}^\xi \end{aligned}$$

$$\varepsilon_{it}^\xi \sim i.i.dN(0, \sigma_\xi^2)$$

- Utility of Work is logarithm of wages

$$U_{it}^w(.) = \ln(w_{it}). = \bar{U}_{it}^w(.) + \varepsilon_{it}^w \text{ with } \varepsilon_{it}^w \sim i.i.dN(0, \sigma_w^2)$$

$$\bar{U}_{it}^w(.) = \varphi_1(S_{it}) + \varphi_2.Exper_{it} + \varphi_3.Exper_{it}^2 + v_i^w$$

- $v_i^w$  is innate market ability
- $v_i^\xi$  is innate taste for schooling (academic ability)
- $v_i^w$  and  $v_i^\xi$  are correlated
- $S_{\max}$  is the maximum schooling achievable and  $T = 65$

- **Key issues:**

- Law of motion is deterministic:

$$S_{it} = \sum_{j=1}^{t-1} d_{it}$$

$$Exper_t = T - S_{it}$$

- Post schooling human capital is exogenous (need to solve for  $S$  only)

$$\Omega_{it} = (S_{it}, \eta_{it}) \text{ and } \eta_{it} = (\varepsilon_{it}^{\xi}, \varepsilon_{it}^w)$$

- However, because random shocks are i.i.d., we will omit them.

## Bellman Equation: Value of Attending School:

$$\begin{aligned} V_t^s(S_t, \eta_t) &= X_i' \delta + \psi(S_{it}) + v_i^\xi + \varepsilon_{it}^\xi + \\ &\beta E(\text{Max}\{V_{t+1}^s(S_{t+1}), V_{t+1}^w(S_{t+1})\} \mid d_t = 1) \\ &= \bar{U}_{it}^s + \varepsilon_{it}^\xi + \beta EV_{t+1}(\cdot \mid d_t = 1) \\ &= \bar{V}_t^s + \varepsilon_{it}^\xi \end{aligned}$$

Define  $\bar{V}_t^s$  as

$$\bar{V}_t^s = X_i' \delta + \psi(S_{it}) + v_i^\xi + \beta EV_{t+1}(\cdot) .$$

**Bellman Equation: Value of entering the labor market:**

$$\begin{aligned} V_t^w(S_t, \eta_t) &= \varphi_1(S_{it}) + \varphi_2 \cdot Exper_{it} + \varphi_3 \cdot Exper_{it}^2 + v_i^w + \varepsilon_{it}^w \\ &\quad + \beta E(V_{t+1}^w(S_{t+1} = S_t) \mid d_t = 0) \\ &= \bar{V}_t^w(S_t, \eta_t) + \varepsilon_{it}^w \end{aligned}$$

Define  $\bar{V}_t^w(S_t, \eta_t)$  as

$$\begin{aligned} \bar{V}_t^w(S_t, \eta_t) &= \varphi_1(S_{it}) + \varphi_2 \cdot Exper_{it} + \varphi_3 \cdot Exper_{it}^2 + \\ &\quad v_i^w + \beta E V_{t+1}^w(S_{t+1}, \eta_{t+1} \mid d_t = 0) \end{aligned}$$

- . Two important thing to note:
- First, at entrance in the market, accumulated experience is 0), so

$$\bar{V}_t^w(S_t, \eta_t) = \varphi_1(S_{it}) + v_i^w + \beta EV_{t+1}^w(S_{t+1}, \eta_{t+1} \mid d_t = 0)$$

- Second, work is an “absorbing” state so no maximization beyond entrance in the market ( $EV_{t+1}^w$  will be a simple sum of discounted earnings)

$$EV_{t+1}^w(.) = \sum_{j=t+1}^T \beta^{j-(t+1)} (\varphi_1(S_j) + \varphi_2 \cdot Exper_j + \varphi_3 \cdot Exper_j^2 + v_i^w)$$

- Obviously, calculating  $EV_{t+1}^w(\cdot)$ , the expected utility of working from  $t+1$  until  $T$ , does not require any maximization.

## Solution

It is now easy to use backward recursions

- Start at  $\tilde{t}$  with  $(S_{\max} - 1)$  years of schooling already accumulated:
- This is the last date at which we need to compute a schooling choice probability because

$$S_{\tilde{t}} = S_{\max} - 1$$



- Either

- $d_{\tilde{t}} = 1$  (obtain  $S_{\max}$  years of schooling and next period start working for  $EV_{\tilde{t}+1}^w(S_{\max}, Exper = 0.)$ )
- $d_{\tilde{t}} = 0$  (obtain  $S_{\max} - 1$  years of schooling, start working in  $\tilde{t}$ , and next period work for  $EV_{\tilde{t}+1}^w(S_{\max} - 1, Exper = 1.)$ )
- Note that both  $EV_{\tilde{t}+1}^w(.)$  is easily computed

- Write down the probabilistic statement ( $\text{Prob } d_{\tilde{t}} = 1$ ) as

$$\begin{aligned}
\Pr(d_{\tilde{t}} = 1) &= \Pr(V_{i\tilde{t}}^s - V_{i\tilde{t}}^w > 0) = \\
&= \Pr\{(X'_i\delta + \psi(S_{\max}) + v_i^\xi + \varepsilon_{it}^\xi + \beta EV_{\tilde{t}+1}^w(S_{\max}, Exper = 0.) \\
&> \varphi_1(S_{\max} - 1) + v_i^w + \varepsilon_{it}^w + EV_{\tilde{t}+1}^w(S_{\max} - 1, Exper = 1.)\} \\
&= \Pr(\varepsilon_{it}^s - \varepsilon_{it}^w > \bar{V}_{i\tilde{t}}^w - \bar{V}_{i\tilde{t}}^s)
\end{aligned}$$

which is simply a non-linear probit equation (conditional on  $v_i^w$  and  $v_i^s$ ).

- Given  $d_{\tilde{t}-1} = 1$ ,

$$EV_{\tilde{t}}(.) = pr(d_{\tilde{t}} = 1) \cdot E(V_{i\tilde{t}}^s \mid V_{i\tilde{t}}^s > V_{i\tilde{t}}^w) + \\ pr(d_{\tilde{t}} = 0) \cdot E(V_{i\tilde{t}}^w \mid V_{i\tilde{t}}^w > V_{i\tilde{t}}^s)$$

- Take one component: say  $E(V_{i\tilde{t}}^s \mid V_{i\tilde{t}}^s > V_{i\tilde{t}}^w)$

$$E(V_{i\tilde{t}}^s \mid V_{i\tilde{t}}^s > V_{i\tilde{t}}^w) \\ = X_i' \delta + \psi(.) + v_i^\xi + \beta EV_{\tilde{t}+1}^w(S_{\max}, Exp = 0) \\ + E\{\varepsilon_{it}^s \mid \varepsilon_{it}^s - \varepsilon_{it}^w > EV_{\tilde{t}+1}^w(S_{\max} - 1, Exp = 1) \\ - \beta EV_{\tilde{t}+1}^w(S_{\max}, Exper = 0.)\}$$

- Evaluating  $E(\varepsilon_{it}^s \mid \varepsilon_{it}^s - \varepsilon_{it}^w > \dots)$  is easily done using standard truncated normal distribution expression (selectivity literature).

- **Digression: Truncated Normal Distributions**

$Z \sim N(\mu, \sigma^2)$ ,  $c$  is a constant (truncation point),  $\alpha = \frac{(c-\mu)}{\sigma}$

$$E(Z \mid Z > c) = \mu + \sigma \cdot \frac{\phi(\alpha)}{(1 - \Phi(\alpha))}$$

$$E(Z \mid Z < c) = \mu - \sigma \cdot \frac{\phi(\alpha)}{\Phi(\alpha)}$$

where the expression,  $\frac{\phi(\alpha)}{(1-\Phi(\alpha))}$ , is often referred to as a **Mill's ratio**.

- In our example:

- $\mu = 0$  (since the  $\varepsilon'$ s have mean 0),

- $\sigma$  is the standard -deviation of  $\varepsilon_{it}^s - \varepsilon_{it}^w$ ,

- $c$  is  $EV_{\tilde{t}+1}^w(S_{\max} - 1, Exper = 1.) - \beta EV_{\tilde{t}+1}^w(S_{\max}, Exper = 0.)$

- Then, evaluate  $E(V_{i\tilde{t}}^w \mid V_{i\tilde{t}}^w > V_{i\tilde{t}}^s) = \dots\dots$

- In the end, you have

$$pr(d_{\tilde{t}} = 1) \cdot E(V_{i\tilde{t}}^s \mid V_{i\tilde{t}}^s > V_{i\tilde{t}}^w) + pr(d_{\tilde{t}} = 0) \cdot E(V_{i\tilde{t}}^w \mid V_{i\tilde{t}}^w > V_{i\tilde{t}}^s)$$

- Going to  $\tilde{t} - 1$ ,

$$V_{\tilde{t}-1}^s = X_i' \delta + \psi(S_{\max} - 1) + v_i^\xi + \varepsilon_{it}^\xi + \beta EV_{\tilde{t}}(\cdot \mid d_{\tilde{t}-1} = 1)$$

$$V_{\tilde{t}-1}^w = \varphi_1(S_{\max} - 2) + v_i^w + \varepsilon_{it}^w + EV_{\tilde{t}+1}^w(S_{\max} - 2, \textit{experience} = 1.)$$

- Proceed recursively until you reach the initial period (say the minimum schooling).

**Estimation is achieved by maximum likelihood.**

- Take an individual with  $\tau$  years of schooling. This individual would have wages observed from  $\tau + 1$  to  $T$
- The Likelihood has 3 parts:
- the probability of having spent at most  $\tau$  years in school, which can be easily derived from the structure of the model

$$L_1 = Pr[(d_0 = 1), (d_1 = 1)....(d_\tau = 1)]$$

- the probability of entering the labor market in year  $\tau + 1$ , at observed wage  $w_{\tau+1}$ , which can be factored as the product of a normal conditional probability times a marginal.

$$L_2 = \Pr(d_{\tau+1} = 0, w_{\tau+1}) = \Pr(d_{\tau+1} = 0 \mid w_{\tau+1}) \cdot \Pr(w_{\tau+1})$$

- the density of observed wages and employment rates from  $\tau + 2$  until 1990.

$$L_3 = Pr(\{w_{\tau+2}\} \cdot .... \Pr\{w_{1990}\})$$



The likelihood function, conditional on  $\vartheta_j = (v^\xi, v^w)_j$ , is given by

$$L_i(\vartheta_j) = L_{1i}(\vartheta_j) \cdot L_{2i}(\vartheta_j) \cdot L_{3i}(\vartheta_j)$$

$$\Pr(v^\xi = v_j^\xi, v^w = v_j^w) = p_j$$

with,

$$p_j = \frac{\exp(p_j^0)}{\sum_{k=1}^{K=6} \exp(p_k^0)}$$

with  $p_6^0 = 0$ .

The unconditional contribution to the log likelihood, for individual  $i$ , is therefore given by

$$\log L_i = \log \sum_{j=1}^{K=6} p_j \cdot L_i(\cdot \mid \vartheta_j)$$

where each  $p_j$  represents the population proportion of type  $\vartheta_j$ .

Estimation provides parameter estimates for all the parameters, including  $\psi(S_{it})$ ,  $v^\xi$ ,  $v^w$  and  $p_j$ .

## NOTES:

- The number of types should go to  $N$  (number of individuals) but this is not feasible.
- The number of types is not a standard parameter (no obvious asymptotic results since you search over a space that has no openness property)
- One approach: Start from large number, and reduce it (the number of types) by likelihood ratio test
- Another approach (to remove arbitrariness): use penalized likelihood approaches using Bayesian criterion.

## Model Simulation:

- First, set a population size (say 10,000 individuals)
- Out of these 10,000 individuals, the population proportions will be given by  $\hat{p}_j$
- Generate 10,000 variates from a uniform distribution, and assign a type to each 10,000 individuals
- for each individual, generate a random shock for each state and each period and solve the problem

- you end-up with 10,000 wage-schooling histories
- Note: you know schooling choices, employment but also  $v_i^\xi$  and  $v_i^w$
- you can evaluate correlation between schooling and  $v_i^\xi, v_i^w$
- you can simulate what would happen if you change  $\varphi_1(S_{it})$

- Belzil and Hansen (2002) use a dynamic programming model to
  - investigate the shape of the wage schooling relationship
  - evaluate ability bias as defined by the correlation between schooling achievement and the individual-specific intercept term of the wage equation.
- The model is implemented on a panel of white males taken from the NLSY covering the years 1979 to 1990.
- BH (2002) deal with the *Convexity of the Wage-Schooling Relationship and the Ability Bias*.  $\varphi_1(S_{it})$  is a non-linear function of  $S_{it}$