- Estimate a simple learning model

- Estimate a simple learning model

- Assume no censoring or truncation

- Estimate a simple learning model

- Assume no censoring or truncation

- Signals are log wage residuals

- Estimate a simple learning model

- Assume no censoring or truncation

- Signals are log wage residuals

- Individuals infer their ability from these residuals

- Estimate a simple learning model

- Assume no censoring or truncation

- Signals are log wage residuals

- Individuals infer their ability from these residuals

$$\log w_{it} = X_{it}\beta + a_i + \varepsilon_{it}$$

What we hope to get out of estimation:

What we hope to get out of estimation:

- Place distributional assumptions on a_i and ε_{it}

What we hope to get out of estimation:

- Place distributional assumptions on a_i and ε_{it}

- Estimate $(\beta, \sigma_a^2, \sigma_\varepsilon^2)$ by maximum likelihood

What we hope to get out of estimation:

- Place distributional assumptions on a_i and ε_{it}

- Estimate $(\beta, \sigma_a^2, \sigma_\varepsilon^2)$ by maximum likelihood

- Recover each person's beliefs at each point in time

What we hope to get out of estimation:

- Place distributional assumptions on a_i and ε_{it}

- Estimate $(\beta, \sigma_a^2, \sigma_\varepsilon^2)$ by maximum likelihood

- Recover each person's beliefs at each point in time

- Compare results with other panel data estimators (FE, RE)

What we hope to get out of estimation:

- Place distributional assumptions on a_i and ε_{it}

- Estimate $(\beta, \sigma_a^2, \sigma_\varepsilon^2)$ by maximum likelihood

- Recover each person's beliefs at each point in time

- Compare results with other panel data estimators (FE, RE)

- Note: our learning model assumes $a_i \perp X_{it}$ so is identical to RE