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

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- Note: our learning model assumes $a_i \perp X_{it}$ so RE estimator can be used