The Consequences of Unobserved Heterogeneity in a Sequential Logit Model

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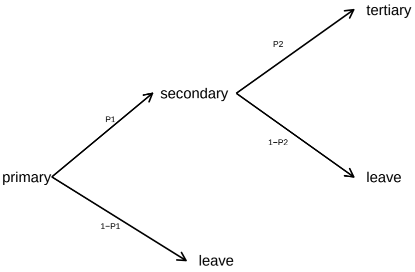
The sequential logit model



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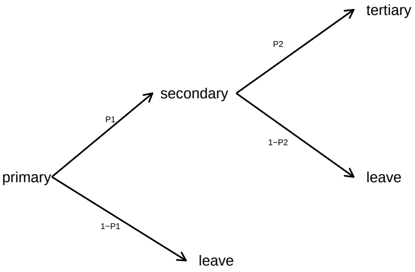

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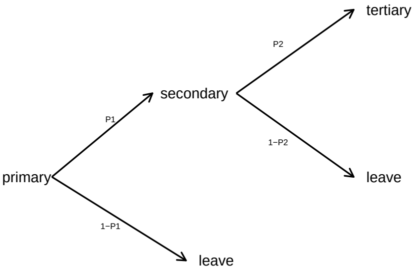

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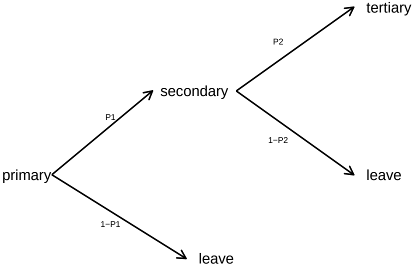

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- $\Lambda(u) = \frac{\exp(u)}{1+\exp(u)}$

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- Use standard logistic regression with these indicator variables as dependent variable.

Outline

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- Even if the unobserved variable(s) are not confounding variables, they will still influence the results through 2 mechanisms:
  - The Averaging Mechanism (scale identification problem)
  - The Selection Mechanism (dynamic selection bias)

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- This means that the unobserved variable is likely to become a confounding variable at higher transitions, even if it was not one at the first transition

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A solution

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- A sensitivity analysis is intended to show which conclusions are robust and which are not.

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  - ε may be non-normally distributed

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