

How	tο	estimate	factor	models?
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- As you know, these vary in their ease of use!

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- Coding walkthrough later

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Likelihood for observation i, assuming $\eta \sim N(0, \sigma_w^2)$ and $\varepsilon_j \sim N(0, \sigma_i^2)$:

$$\mathcal{L}_{i} = \left\{ \prod_{j} \frac{1}{\sigma_{j}} \phi \left(\frac{asvab_{ij} - W_{i}\alpha_{j} - \gamma_{j}\xi_{i}}{\sigma_{j}} \right) \right\} \frac{1}{\sigma_{w}} \phi \left(\frac{\log(wage_{i}) - X_{i}\beta - \delta\xi_{i}}{\sigma_{w}} \right)$$

Since ξ is unobserved, integrate out: $\ell = \sum_{i} \log \left(\int \mathcal{L}_{i} dF(\xi) \right)$

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• Reminiscent of mixed logit / preference heterogeneity