Ordered Probit / Ordered Logit

Modeling Outcomes That Have a Ranking but Not a Scale

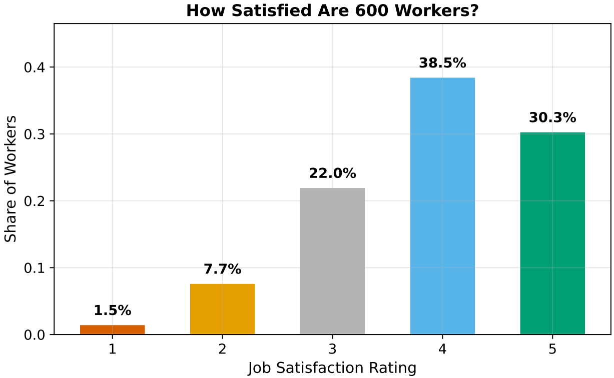
Jake Anderson

May 16, 2026

Outline

The Data

A firm surveys **600 workers** about job satisfaction. Each worker reports a rating from 1 (very dissatisfied) to 5 (very satisfied).



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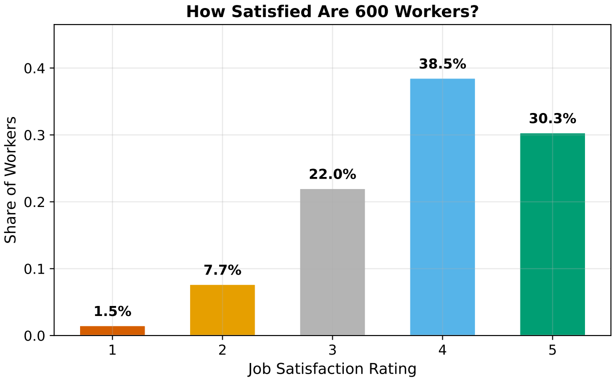
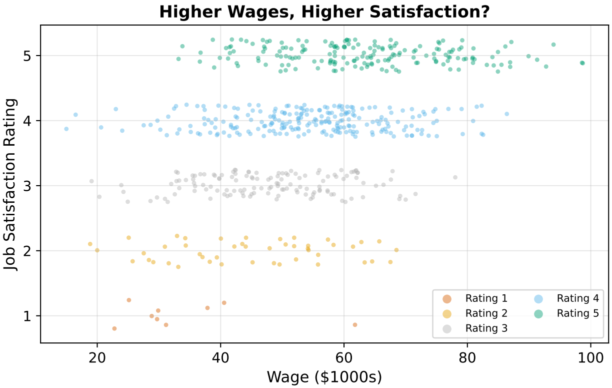


The outcome is **ordinal**: $5 > 4 > 3 > 2 > 1$, but the distances between categories are not meaningful. Is the gap from 1 to 2 the same as 4 to 5?

Does Wage Predict Satisfaction?



Does Wage Predict Satisfaction?

Higher-paid workers tend to report higher ratings. But the outcome takes only five discrete values. How should we model this?

First Instinct: Run OLS

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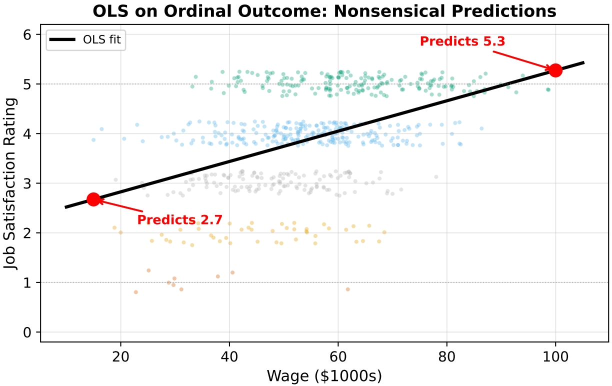
This is fast and gives a slope you can interpret. What could go wrong?

OLS on Ordinal Outcomes: The Failure



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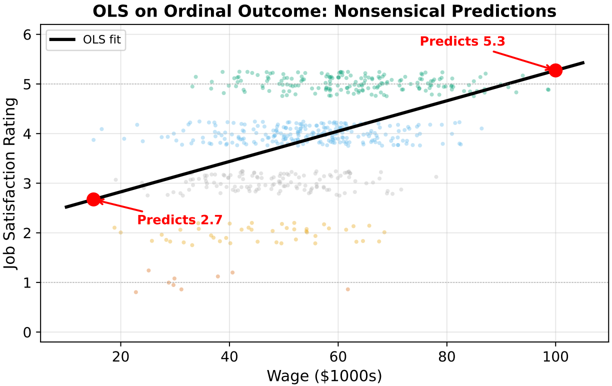

At high wages, OLS predicts **5.3**. But the scale only goes to 5. At low wages, it predicts non-integer values between categories. OLS treats ordinal categories as if they were continuous and equally spaced.

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$\Longrightarrow$ We need a model that respects the ordinal nature of the outcome: categories have a ranking, but the distances between them are unknown.

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$\Longrightarrow$ Where can we find a model with these properties?

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$\Longrightarrow$ This is the latent variable approach: posit an unobserved continuous satisfaction level, then map it to the observed categories through thresholds.

Outline

The Idea: A Continuous Variable Behind Discrete Ratings

Imagine each worker has a latent (unobserved) satisfaction level y_i^* that is continuous:

$$y_i^* = \beta_1 \, \text{Wage}_i + \beta_2 \, \text{Hours}_i + \beta_3 \, \text{Support}_i + \varepsilon_i$$

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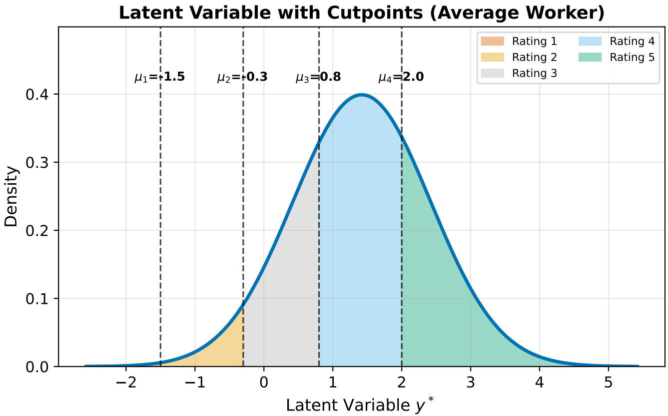
The mapping from y_i^* to the observed rating uses **cutpoints** $\mu_1 < \mu_2 < \mu_3 < \mu_4$:

$$\text{Rating}_i = j \quad \iff \quad \mu_{j-1} < y_i^* \leq \mu_j$$

where $\mu_0 = -\infty$ and $\mu_5 = +\infty$.

Cutpoints Partition the Latent Variable



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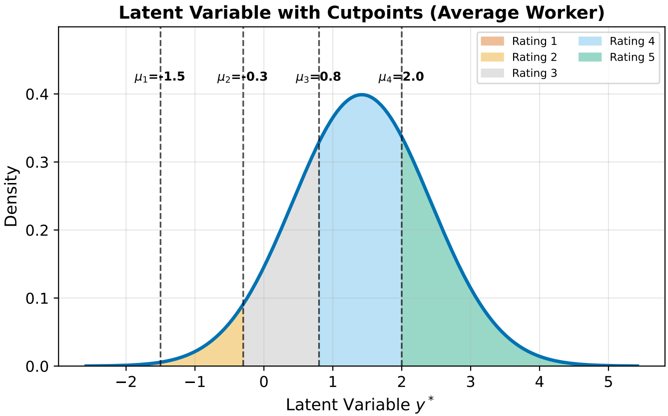

The density of y_i^* is divided into five regions by four cutpoints. The area in each region equals the probability of that rating.

How Covariates Shift the Distribution

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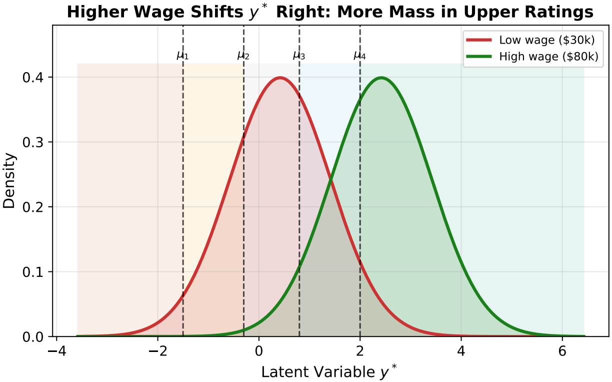

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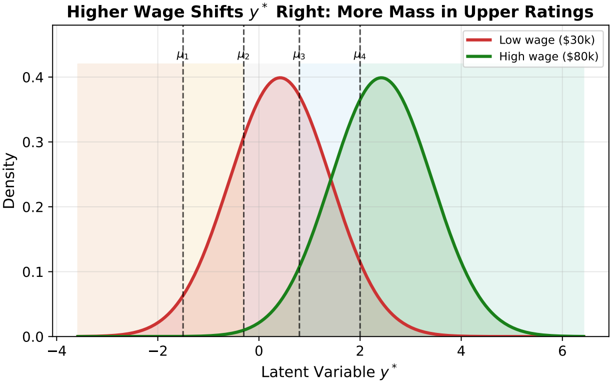

The cutpoints stay fixed; the density moves. Positive β raises $P(\text{highest})$ and lowers $P(\text{lowest})$; middle categories are ambiguous.

The Probability Formula: Derivation

The probability of observing rating j depends on where y_i^* falls:

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with boundary conditions $F(-\infty) = 0$ and $F(+\infty) = 1$.

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$\Longrightarrow$ Same idea, different distributional assumption on ε_i. Results are usually similar in practice. Economists tend to use ordered probit; biostatisticians often prefer ordered logit.

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There is **no intercept** in the equation. An intercept would be absorbed into the cutpoints (you cannot separately identify both), so we normalize by omitting it.

The Parallel Regressions Assumption

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$\Longrightarrow$ This is what makes the ordered model parsimonious: one set of slopes instead of four.

Numeric Example: Computing Probabilities

Suppose a worker earns \$55k, works 42 hours, and has supervisor support $(= 1)$. With the ordered probit coefficients $\beta_{\text{wage}} = 0.04$, $\beta_{\text{hours}} = -0.03$, $\beta_{\text{support}} = 0.80$:

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$\Longrightarrow$ This worker has a 42.9% chance of reporting "Satisfied" (Rating 4). Software computes all five probabilities simultaneously.

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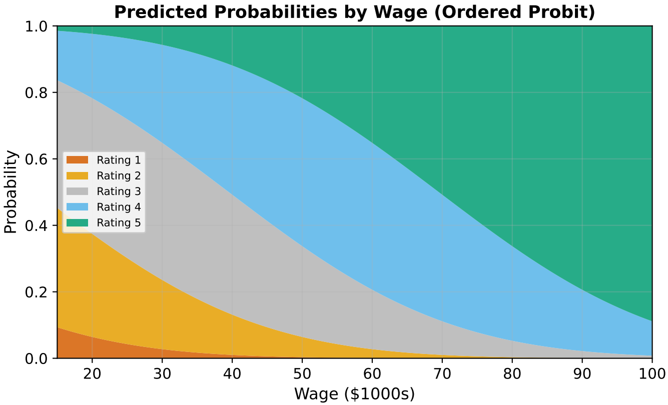

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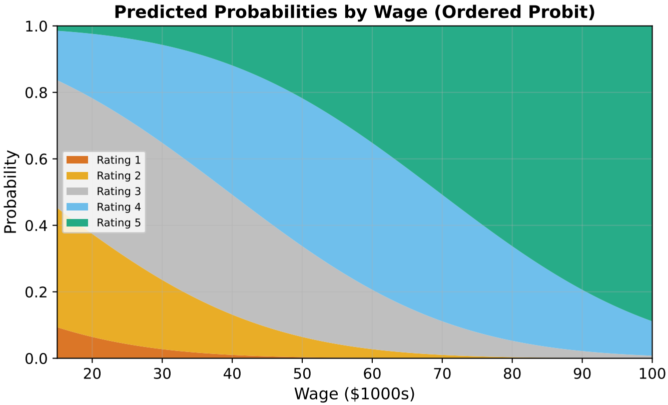

As wage increases, probability shifts from lower ratings to higher ratings. At every wage level, the five probabilities sum to 1.

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For magnitudes, compute **marginal effects** on probabilities.

Marginal Effects: The Formula

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For the **extreme categories**, one of the boundary terms drops out:

- Rating 1: $\text{ME} = -f(\mu_1 - \text{XB}_i) \cdot \beta_k$ ($\beta_k > 0 \implies$ negative)
- Rating 5: $\text{ME} = f(\mu_4 - \text{XB}_i) \cdot \beta_k$ ($\beta_k > 0 \implies$ positive)

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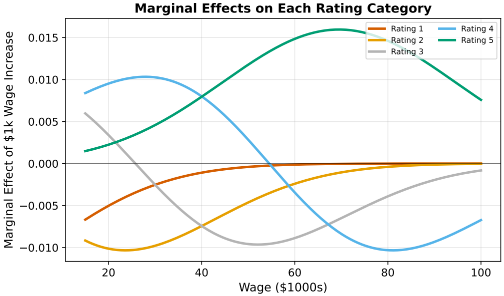
$\implies$ A positive coefficient always decreases $P(\text{lowest})$ and increases $P(\text{highest})$. But what about the middle categories?

Middle Categories: Ambiguous Marginal Effects



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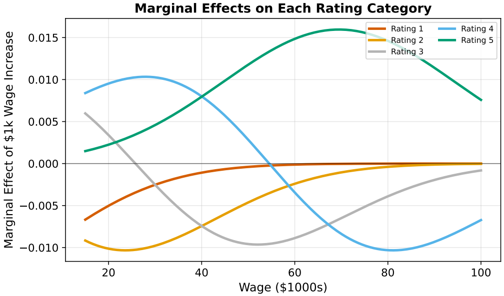

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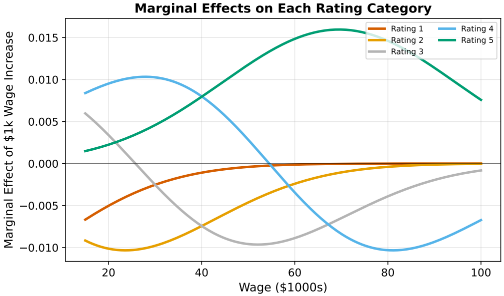

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$\Longrightarrow$ Report Average Marginal Effects (AMEs) for each category, not just the coefficient.

Estimation: Maximum Likelihood

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The log-likelihood:

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$\implies$ Software estimates the coefficients and the cutpoints jointly.

Outline

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$\implies$ Using multinomial logit on ordered data wastes the ordering information and estimates far more parameters than necessary ($J - 1$ coefficient vectors instead of one).

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$\Longrightarrow$ Always check parallel regressions before reporting ordered model results.

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$\Longrightarrow$ In practice, both give very similar results. Choose based on convention in your field.

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$\Longrightarrow$ The ordered model is more efficient than multinomial logit when the ordering is genuine, because it estimates fewer parameters while exploiting the ranking structure.

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Recall the three OLS problems. How does ordered probit address each one?

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$\Longrightarrow$ Interpret the sign of $\hat{\beta}$ for direction; compute AMEs for magnitude. Check the parallel regressions assumption before reporting.

Thank you!

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