

Applied Regression (II)

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Applied Quantitative Methods II

IC3JM, Spring 2026

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- Understand non-linear relationships
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- Discuss how to present and interpret results

Roadmap

Interaction Effects

When effects depend on context

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- We model this with **interaction terms**

The interaction model

$$Y = \beta_0 + \beta_1 X + \beta_2 Z + \beta_3 (X \times Z) + \varepsilon$$

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- β_2 : effect of Z when $X = 0$
- β_3 : how the effect of X changes as Z increases

The marginal effect of X

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- Need to report effects at meaningful values of Z

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- Packages like `marginalEffects` make this easy in R

Roadmap

Non-linear Relationships

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 - β_1 is an elasticity: 1% change in $X \rightarrow \beta_1\%$ change in Y

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- Always check if the transformation makes sense substantively

Roadmap

Inference: Standard Errors and Hypothesis Testing

What are standard errors?

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- Smaller SE = more confidence in our estimate

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- Intuition: We learn more from larger, more varied samples with less noise

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- **Not:** “There’s a 95% probability β is in this interval”

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- p-value: Probability of seeing this (or more extreme) result if H_0 is true

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- But H_0 compatible doesn't mean H_0 is true!

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- Practical significance: “Is the effect large enough to matter?”
- With enough data, tiny effects become “significant”
- A large sample can detect effects too small to care about
- Always consider the **size** of the effect, not just significance

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- Always report robust SEs unless you have good reason not to

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Presenting Results

Principles for presenting regression results

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- Help readers understand the **size** of effects

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- The `marginalEffects` package in R is excellent for this

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 - “Going from high school to college increases income by \$Z”

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 - Report mean and percentiles (95% CI)
- Propagates uncertainty properly through calculations

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- Standard errors measure estimation precision
- p-values are about data, not hypothesis probability
- Present results as interpretable quantities, not just coefficients

For next week

- Read King et al. (2000), “Making the most of statistical analyses”
 - Read Brambor et al. (2006), “Understanding Interaction Models”
 - Check out marginaleffects.com
 - Complete Problem Set 2
-
- Next session: Model interpretation and diagnostics

Questions?