Marginal odds ratios

Marginal Odds Ratios: What They Are, How to Compute Them, and Why Sociologists Might Want to Use Them

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Outline

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Background

- Due to concerns regarding their interpretation, odds ratios have fallen out of favor in sociology. Average marginal effects (AME) or linear probability models (LMP) are now the standard.
  - Analysis of papers published in the *American Sociological Review*:

	2010–2015	2016–2021
"odds ratio"	32	9
"marginal effect"	2	11
"linear probability model"	3	16

- But this might be throwing out the baby with the bathwater, because . . .

  . . . magnitudes of AMEs likely depend on the margin,

  . . . AMEs focus on absolute probability differences, not relative differences, which are key to much theory and research in sociology.

Background

- What we suggest (Karlson and Jann 2023):

  Use **marginal (log) odds ratios**, which ...

  ... behave like AME but retain the (relative) odds ratio interpretation!

  - ✔ unaffected by noncollapsibility
  - ✔ an average effect (population-averaged)
  - ✔ comparable across populations/studies

Marginal odds ratio

- Following Zhang (2008) and Daniel et al. (2021) we use potential outcomes notation to define the marginal odds ratio.
- Y_t: Potential outcome that would realize if treatment T was set to level t by manipulation (i.e., without changing anything else).
- We focus on *binary* outcomes only, that is, $Y_t \in \{0, 1\}$ (failure or success).
- Thus:

  $\text{Pr}(Y_t = 1) = E[Y_t]$ is the (marginal) probability that Y_t will be equal to 1 (probability of success).

Marginal odds ratio

- Consider a binary treatment $T \in \{0, 1\}$.
- The marginal odds ratio (MOR) of the alternative treatment ($T = 1$) versus the standard treatment ($T = 0$) is defined as

$$\mathrm{MOR} = \frac{\mathrm{odds}(\Pr[Y_1 = 1])}{\mathrm{odds}(\Pr[Y_0 = 1])}$$

  where $\mathrm{odds}(p)$ stands for $p/(1-p)$.
- Interpretation of MOR: The ratio of the odds of success if everyone would receive the alternative treatment versus the odds of success if everyone would receive the standard treatment (assuming that there are no general equilibrium effects, i.e., SUTVA holds).

"Marginal" refers to how a predictor affects the "marginal distribution" of an outcome (i.e., not to a marginal change in a predictor). "Unconditional" would be another term but we use "marginal" because the term is established in the literature (Stampf et al. 2010; Karlson, Popham, and Holm 2021).

Adjusting for covariates

- The probability of success may not only depend on T, but also on other factors $\mathbf{X}$.
- Assume that $\mathbf{X}$ has a specific distribution in the population and let $\Pr(Y_t = 1|\mathbf{X} = \mathbf{x}) = E[Y_t|\mathbf{X} = \mathbf{x}]$ be the conditional success probability given $\mathbf{X} = \mathbf{x}$.
- By the law of iterated expectations,

$$\Pr(Y_t = 1) = E_{\mathbf{X}}[\Pr(Y_t = 1|\mathbf{X} = \mathbf{x})]$$

where $E_{\mathbf{X}}$ is the expectation over the distribution of $\mathbf{X}$.

Adjusting for covariates

- The marginal odds ratio, adjusting for $\mathbf{X}$, can then be written as

$$\text{MOR} = \frac{\text{odds}(\Pr[Y_1 = 1])}{\text{odds}(\Pr[Y_0 = 1])} = \frac{\text{odds}\{E_{\mathbf{X}}[\Pr(Y_1 = 1|\mathbf{X} = \mathbf{x})]\}}{\text{odds}\{E_{\mathbf{X}}[\Pr(Y_0 = 1|\mathbf{X} = \mathbf{x})]\}}$$

- We term this the *adjusted* MOR.
- Note:
  - The adjusted MOR is the same as the unadjusted MOR by definition (i.e., same estimand)!
  - However, estimation based on the adjusted MOR formulation can be used to address confounding bias in observational data. It can also be used to increase efficiency in analysis of randomized experiments.
  - Close relationship to AME, which is defined as

$$\text{AME} = E_{\mathbf{X}}[\Pr(Y_1 = 1|\mathbf{X} = \mathbf{x})] - E_{\mathbf{X}}[\Pr(Y_0 = 1|\mathbf{X} = \mathbf{x})]$$

▸ Continuous treatments ▸ Estimation

Relationship to the logistic model

- Consider a simple logistic model

$$\Pr(Y_t = 1) = \text{logistic}(\alpha + \delta t) \quad \text{where} \quad \text{logistic}(z) = \frac{\exp(z)}{1 + \exp(z)}$$

which implies

$$\ln \text{odds}(\Pr[Y_t = 1]) = \alpha + \delta t$$

- Assume T is binary. We then recover the MOR as

$$\begin{aligned} \text{MOR} &= \exp\{\ln \text{odds}(\Pr[Y_t = 1]) - \ln \text{odds}(\Pr[Y_0 = 1])\} \\ &= \exp\{(\alpha + \delta) - (\alpha)\} = \exp(\delta) \end{aligned}$$

- Meaning: the (exponent of the) slope coefficient in a simple logistic regression estimates the MOR

  (The same also holds in case of a continuous treatment, which is easy to show.)

Relationship to the logistic model

- If we condition on $\mathbf{X}$, then

$$\Pr(Y_t = 1|\mathbf{X} = \mathbf{x}) = \text{logistic}(\alpha + \delta t + \mathbf{x}\beta)$$

- Here $\exp(\delta)$ is the *conditional* odds ratio (i.e., the odds ratio within a subgroup defined by a specific value of $\mathbf{X}$). For a binary treatment:

$$\text{COR} = \frac{\text{odds}\{\text{logistic}(\alpha + \delta + \mathbf{x}\beta)\}}{\text{odds}\{\text{logistic}(\alpha + \mathbf{x}\beta)\}} = \exp(\delta)$$

- The conditional odds ratio (COR) is different from the MOR, which has a more involved form. For example, in case of a binary treatment:

$$\text{MOR} = \frac{\text{odds}\{E_{\mathbf{X}}[\text{logistic}(\alpha + \delta + \mathbf{x}\beta)]\}}{\text{odds}\{E_{\mathbf{X}}[\text{logistic}(\alpha + \mathbf{x}\beta)]\}}$$

This will be different from COR when $\beta \neq \mathbf{0}$.

Relationship to the logistic model

- The difference between MOR and COR is referred to as *noncollapsibility* or *rescaling bias* (MOR will be attenuated compared to COR).
- An important insight is that MOR and COR are conceptually different. They correspond to different estimands!
- We prefer MOR over COR because
  1. there is just one MOR but many CORs,
  2. the MOR has an interpretation similar to an AME on the probability scale ("population response" to a treatment),
  3. the MOR can be used to compare results from different models and samples/populations.

Academic ability and intergenerational college mobility

- Comparison of “secondary effects” of family background on educational attainment between the United States (National Longitudinal Survey of Youth, 1979 cohort) and Denmark (Danish Longitudinal Survey of Youth).
- How much does educational attainment (here: going to college) depend one whether parents have college education, once we control for academic ability (the “primary effect”)?

Academic ability and intergenerational college mobility

Odds ratios of parental college attainment gap in college attainment unadjusted and adjusted for academic ability. The United States and Denmark. Standard errors in parentheses.

	USA (N = 10,068)	**DNK** (N = 2,185)	**USA/DNK**
Unadjusted odds ratio	7.7 (0.46)	3.8 (0.55)	2.03*
Conditional odds ratio adjusted for academic ability	3.4 (0.23)	2.9 (0.45)	1.17
Marginal odds ratio adjusted for academic ability	2.5 (0.13)	2.5 (0.33)	1.00

Notes: US data are from the NLSY79; the Danish data are from the Danish Longitudinal Survey of Youth. * indicates that the country difference in log odds ratios is statistically significant at a five percent level.

(Karlson and Jann 2023)

Academic ability and intergenerational college mobility

- The unadjusted or gross marginal odds ratio is about twice as large in the US as in Denmark, meaning that Denmark is significantly more educationally mobile.
- However, the “secondary effects” of family background are of similar magnitude in the two countries (adjusted marginal odds ratio). This means that academic ability “mediates” a significantly larger portion of the overall effect in the US than in Denmark.
- Had we been using the conditional odds ratio, we would have concluded that, net of academic ability, Denmark is a (albeit only slightly) more educationally mobile country than the US.
- This is because the attenuating impact of noncollapsibility is more pronounced in the US than in Denmark (since academic ability is a much stronger predictor of college attainment in the US).

College gap in attitudes toward racial segregation

- Analysis of how the gap in attitudes toward racial segregation between respondents with and without a four-year college degree changed over time.
- General Social Survey cumulative file, 1976–1996
- Outcome: Agreement with claim that white people have a right to keep black people out of their neighborhoods.
- Predictor of interest: college attainment
- Controls: survey year, age, gender, race, marital status, liberal–conservative scale
- Joint model across time points with survey year fully interacted with college attainment and all other covariates; we obtain AMEs and MORs from the model at different years.

College gap in attitudes toward racial segregation

Average marginal effects and marginal odds ratios of the college gap in the attitude toward racial segregation in 1976, 1981, 1986, 1991, and 1996. Standard errors in parentheses.

	AME	**ln(MOR)**
1976	-0.213	-1.006
1981	-0.181	-0.983
1986	-0.147	-0.959
1991	-0.115	-0.934
1996	-0.088	-0.909
1976–1996 difference	0.125 (0.028)	0.097 (0.211)
1976–1996 proportional reduction	58.5%	9.7%

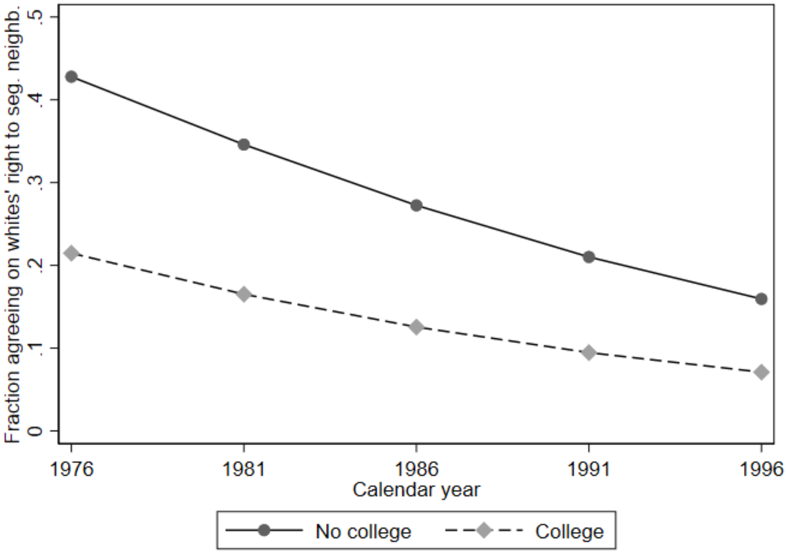
Note: MOR is marginal odds ratio; AME is average marginal effect. Estimates are adjusted for gender, race, age, marital status, and overall political view. Data are from General Social Surveys Cumulative File, N = 12,239.

(Karlson and Jann 2023)

College gap in attitudes toward racial segregation

- Main finding is that the absolute college gap (as measured by the AME) in the attitude toward racial segregation has declined significantly over the 20-year period, whereas the relative gap (as measured by the MOR) remained practically unchanged.
- The absolute gap reduced over time because there is a general decline in support of racial segregation, and this decline is steeper among the non-college educated in absolute terms because they start at a higher level than the college educated. However, the relative difference does not change much (see figure).
- The example illustrates how the MOR can be an informative complement to the AME.

College gap in attitudes toward racial segregation



(Karlson and Jann 2023)

Discussion

- We provide a clear definition of the marginal OR (clarification of estimand).
- We illustrate the advantages of the marginal odds ratio over the conditional odds ratio; we illustrate the value of the marginal odds ratio as a complement to AMEs.
- We provide flexible software that can estimate the marginal OR for categorical as well as continuous predictors (including support for complex surveys).
- But . . .

  . . . is it worth the hassle? How much do sociologists love odds ratios?

  . . . will it change practice?

References

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Appendix: Continuous treatments

- In case of a continuous treatment, the MOR may depend on the level of the treatment (i.e., MOR may not be constant).
- We define the level-specific marginal log odds ratio as the derivative of the marginal log odds by the treatment:

$$\begin{aligned}\ln \mathrm{MOR}(t) &= \lim_{\epsilon\to 0} \frac{\ln \mathrm{odds}[\Pr(Y_{t+\epsilon}=1)] - \ln \mathrm{odds}[\Pr(Y_t=1)]}{\epsilon} \\ &= \lim_{\epsilon\to 0} \frac{\begin{array}{l}\ln \mathrm{odds}\{E_{\mathbf{X}}[\Pr(Y_{t+\epsilon}=1|\mathbf{X}=\mathbf{x})]\} \\ \qquad - \ln \mathrm{odds}\{E_{\mathbf{X}}[\Pr(Y_t=1|\mathbf{X}=\mathbf{x})]\}\end{array}}{\epsilon}\end{aligned}$$

- We can then obtain the average MOR by integrating over the distribution of T:

$$\overline{\mathrm{MOR}} = \exp\{E_T[\ln \mathrm{MOR}(t)]\}$$

Appendix: Continuous treatments

- Another possibility is to integrate over T when obtaining the population-averaged probabilities, that is,

$$\ln \mathrm{MOR}' = \lim_{\epsilon \to 0} \frac{\ln \mathrm{odds}\{E_T[\Pr(Y_{t+\epsilon} = 1)]\} - \ln \mathrm{odds}\{E_T[\Pr(Y_t = 1)]\}}{\epsilon}$$
$$= \lim_{\epsilon \to 0} \frac{\ln \mathrm{odds}\{E_{T,\mathbf{X}}[\Pr(Y_{t+\epsilon} | \mathbf{X} = \mathbf{x})]\} - \ln \mathrm{odds}\{E_{T,\mathbf{X}}[\Pr(Y_t | \mathbf{X} = \mathbf{x})]\}}{\epsilon}$$

- This corresponds to the marginal odds ratio that is obtained if treatment is slightly increased for each population member, given the member's existing values for T and $\mathbf{X}$.

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Appendix: Estimation

- Estimand $\Rightarrow$ Estimation
- There are several approaches how we can estimate the MOR.
  - G-computation (using predictions from a model)
  - Inverse probability weighting
  - Unconditional logistic regression (RIF regression)
- All are discussed in detail in Jann and Karlson (2023) (for binary/categorical as well as continuous treatments; including formulas for analytic standard errors based on influence functions).
- Our preferred method is G-computation as it closely resembles the formulation of the adjusted MOR above. That is, G-computation obtains the MOR that is *implied* by the chosen logit model. The other methods follow a somewhat different logic.

▸ G-computation ▸ Software ▸ Applied example ▸ Simulation results

◂ Return

Appendix: G-computation

- G-computation estimates the MOR using counterfactual predictions from a logit model (or any other model in principle).
- For example, for a binary treatment, the procedure is as follows.
  1. Regress Y on T and $\mathbf{X}$ using logistic regression (or, in principle, any other model).
  2. Use the model estimates to generate two predictions of $\Pr(Y = 1)$ for each observation, one with T set to 0 and one with T set to 1.
  3. Predictions are then averaged across the sample to obtain estimates of the population-averaged success probability by treatment level.
  4. These average predictions can then be plugged into the formula for the MOR:

$$\ln \widehat{\text{MOR}} = \ln \text{odds}(\overline{p}^{T=1}) - \ln \text{odds}(\overline{p}^{T=0})$$

- Note that, in Stata, `margins` followed by `nlcom` can be used to do the above computations in case of a binary treatment.

Appendix: G-computation

- For continuous treatments we evaluate level-specific MORs (using analytic derivatives) at each level of the treatment (possibly using an approximation grid) and then average over the treatment distribution (not directly possible with `margins`).
- An alternative approach is based on applying fractional logit to averaged counterfactual predictions at each value of T. For binary/categorical treatments this leads to the same results as the procedure above. For continuous treatments results slightly differ (due to the different implicit averaging). Nonetheless we prefer this approach due to its generality and flexibility.

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Appendix: Software

- We provide three Stata packages for the estimation of marginal odds ratios, each implementing one of the three approaches. All packages provide consistent standard errors and support complex survey estimation.
  - `lnmor`: G-computation (https://github.com/benjann/lnmor)
  - `ipwlogit`: Inverse probability weighting (https://github.com/benjann/ipwlogit)
  - `riflogit`: Unconditional logistic regression (https://github.com/benjann/riflogit)
- Installation:
  - Type

    `ssc install` *name*`, replace`

    where *name* is the package name.

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Appendix: Applied example

- Application: gender gap in STEM

```
. use stem, clear
(Excerpt from TREE cohort 2)

. describe

Contains data from stem.dta
 Observations:         6,809                  Excerpt from TREE cohort 2
    Variables:             7                  11 Jan 2023 11:05
--------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
--------------------------------------------------------------------------------
stem            byte    %8.0g                 Is in STEM training
male            byte    %8.0g                 Is male
mathscore       double  %10.0g                Math score
repeat          byte    %8.0g                 Ever repeated a grade
books           byte    %19.0g     books      Number of books at home
wt              double  %10.0g                Sampling weight
psu             int     %8.0g                 Sampling unit
--------------------------------------------------------------------------------
Sorted by:
```

Appendix: Applied example

- Probability difference

```
. mean stem [pw=wt], over(male) cluster(psu)
Mean estimation                           Number of obs = 6,809
                  (Std. err. adjusted for 800 clusters in psu)
--------------------------------------------------------------
             |             Robust
             |       Mean   std. err.     [95% conf. interval]
-------------+------------------------------------------------
 c.stem@male |
          0  |   .1632341   .0093646      .1448519    .1816163
          1  |   .2748702    .014516      .2463762    .3033643
--------------------------------------------------------------

. regress stem i.male [pw=wt], cluster(psu) noheader
(sum of wgt is 78,600.15)
                                (Std. err. adjusted for 800 clusters in psu)
----------------------------------------------------------------------------
             |               Robust
        stem | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+--------------------------------------------------------------
      1.male |   .1116361   .0142969     7.81   0.000     .0835721       .1397
       _cons |   .1632341   .0093653    17.43   0.000     .1448506    .1816177
----------------------------------------------------------------------------
```

Appendix: Applied example

- Unadjusted (gross) OR

```
. logit stem i.male [pw=wt], or cluster(psu) nolog

Logistic regression                                     Number of obs =  6,809
                                                        Wald chi2(1)  =  67.37
                                                        Prob > chi2   = 0.0000
Log pseudolikelihood = -40949.271                       Pseudo R2     = 0.0172

                                  (Std. err. adjusted for 800 clusters in psu)
------------------------------------------------------------------------------
             |               Robust
        stem | Odds ratio   std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
      1.male |   1.943143   .1572675     8.21   0.000     1.658109    2.277176
       _cons |   .1950775   .0133747   -23.84   0.000     .1705485    .2231342
------------------------------------------------------------------------------
Note: _cons estimates baseline odds.
```

Appendix: Applied example

- Conventional approach: "conditional" OR

```
. logit stem i.male mathscore i.repeat books [pw=wt], or cluster(psu) nolog
Logistic regression                                   Number of obs =  6,809
                                                      Wald chi2(4)  = 596.06
                                                      Prob > chi2   = 0.0000
Log pseudolikelihood = -31906.84                      Pseudo R2     = 0.2342
                                   (Std. err. adjusted for 800 clusters in psu)
```

stem	Odds ratio	Robust std. err.	z	P>|z|	[95% conf.	interval]
1.male	1.959347	.167555	7.87	0.000	1.656991	2.316874
mathscore	2.605975	.1251954	19.94	0.000	2.371795	2.863278
1.repeat	.6564493	.0965051	-2.86	0.004	.4921137	.8756628
books	1.086996	.0341203	2.66	0.008	1.022137	1.155971
_cons	.1058298	.0166896	-14.24	0.000	.0776911	.1441599

Note: _cons estimates baseline odds.

Appendix: Applied example

- G-computation approach (`lnmor` is a post-estimation command, i.e. first estimate the model, then apply `lnmor`)

```
. lnmor i.male, or
Enumerating predictions: male..done
Marginal odds ratio                                 Number of obs     =      6,809
                                                    Command           =      logit
                                  (Std. err. adjusted for 800 clusters in psu)
------------------------------------------------------------------------------
             |               Robust
        stem | Odds Ratio   std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
      1.male |   1.677102   .1103147     7.86   0.000     1.473958    1.908244
------------------------------------------------------------------------------
```

Appendix: Applied example

- Compare results (SEs in parentheses)

ln(MOR)	Unadjusted	Conditional	Adjusted
1.male	0.664	0.673	0.517
	(0.0809)	(0.0855)	(0.0658)

MOR	Unadjusted	Conditional	Adjusted
1.male	1.943	1.959	1.677
	(0.157)	(0.168)	(0.110)

Appendix: Applied example

- Could also do a statistical test for confounding!

```
. quietly logit stem i.male [pw=wt], cluster(psu)
. quietly lnmor i.male, nodots rif(RIF*)
. quietly logit stem i.male mathscore i.repeat books [pw=wt], cluster(psu)
. quietly lnmor i.male, nodots rif(RIFadj*)
. quietly total RIF2 RIFadj2 [pw=wt], cluster(psu)
. lincom RIFadj2 - RIF2
 ( 1)  - RIF2 + RIFadj2 = 0
```

Total	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
(1)	-.1472398	.042049	-3.50	0.000	-.2297794	-.0647002

```
. drop RIF*
```

Appendix: Applied example

- Some further functionality: Obtain results for several predictors in one call

```
. logit stem i.male mathscore i.repeat books [pw=wt], cluster(psu)
```

(*output omitted*)

```
. lnmor i.male mathscore i.repeat books, or
(mathscore has 380 levels; using 82 binned levels)

Enumerating predictions: male..mathscore....................................
..........................................repeat..books......done

Marginal odds ratio                              Number of obs     =      6,809
                                                 Command           =      logit

                                    (Std. err. adjusted for 800 clusters in psu)
```

stem	Odds Ratio	Robust std. err.	t	P>|t|	[95% conf.	interval]
1.male	1.677102	.1103147	7.86	0.000	1.473958	1.908244
mathscore	2.544088	.1227496	19.35	0.000	2.314196	2.796817
1.repeat	.7244886	.0838845	-2.78	0.006	.5771998	.9093623
books	1.065503	.0258046	2.62	0.009	1.016036	1.11738

Appendix: Applied example

- Some further functionality: Using `at()` to evaluate interactions

```
. logit stem i.male##c.mathscore##c.mathscore##i.repeat##c.books [pw=wt], ///
>     cluster(psu)
```

(*output omitted*)

```
. lnmor i.male, nodots or at(repeat)

Marginal odds ratio                                  Number of obs     =      6,809
                                                     Command           =      logit

Evaluated at:
    1: repeat = 0
    2: repeat = 1

                                  (Std. err. adjusted for 800 clusters in psu)
```

stem	Odds Ratio	Robust std. err.	t	P>|t|	[95% conf.	interval]
1						
1.male	1.700848	.1254404	7.20	0.000	1.47161	1.965795
2						
1.male	1.514373	.3346268	1.88	0.061	.9814315	2.336716

Appendix: Applied example

- Some further functionality: Using `at()` to evaluate interactions

```
. lnmor i.male, nodots or at(mathscore = -2(2)2)
Marginal odds ratio                             Number of obs     =      6,809
                                                Command           =      logit

Evaluated at:
    1: mathscore = -2
    2: mathscore = 0
    3: mathscore = 2
                                  (Std. err. adjusted for 800 clusters in psu)
```

stem	Odds Ratio	Robust std. err.	t	P>|t|	[95% conf.	interval]
1						
1.male	1.697881	.6743511	1.33	0.183	.7786114	3.702489
2						
1.male	1.890371	.2008559	5.99	0.000	1.534504	2.328768
3						
1.male	1.992419	.356629	3.85	0.000	1.402137	2.831202

Appendix: Applied example

- Some further functionality: Analyze nonlinear effects

```
. logit stem i.male c.mathscore##c.mathscore i.repeat c.books [pw=wt], ///
>     cluster(psu)
```

(*output omitted*)

```
. lnmor c.mathscore##c.mathscore
(mathscore has 380 levels; using 82 binned levels)
Enumerating predictions: mathscore...........................................
......................................done
Marginal log odds ratio                              Number of obs     =      6,809
                                                     Command           =      logit
                                   (Std. err. adjusted for 800 clusters in psu)
```

stem	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
mathscore	1.0229	.0698468	14.64	0.000	.8857948	1.160005
c.mathscore# c.mathscore	-.0757576	.0276335	-2.74	0.006	-.1300004	-.0215148

Appendix: Applied example

- Some further functionality: Analyze nonlinear effects by obtaining level-specific MORs using option `dx()`

```
. lnmor mathscore, or dx(-3(1)3)
Enumerating predictions: mathscore.......done
Marginal odds ratio                              Number of obs     =      6,809
                                                 Command           =      logit
                                                 Type of dx()      =     levels
                                     (Std. err. adjusted for 800 clusters in psu)
```

stem	Odds Ratio	Robust std. err.	t	P>|t|	[95% conf.	interval]
mathscore@l1	4.424869	1.003165	6.56	0.000	2.835509	6.905096
mathscore@l2	3.805942	.6538704	7.78	0.000	2.71645	5.332398
mathscore@l3	3.259636	.385185	10.00	0.000	2.584828	4.110613
mathscore@l4	2.779552	.1943118	14.62	0.000	2.423143	3.188383
mathscore@l5	2.378328	.1147795	17.95	0.000	2.163366	2.61465
mathscore@l6	2.056595	.1576843	9.40	0.000	1.769237	2.390626
mathscore@l7	1.788865	.2248208	4.63	0.000	1.397778	2.289376

```
Terms affected by dx(): mathscore
Levels of dx(): -3 -2 -1 0 1 2 3
```

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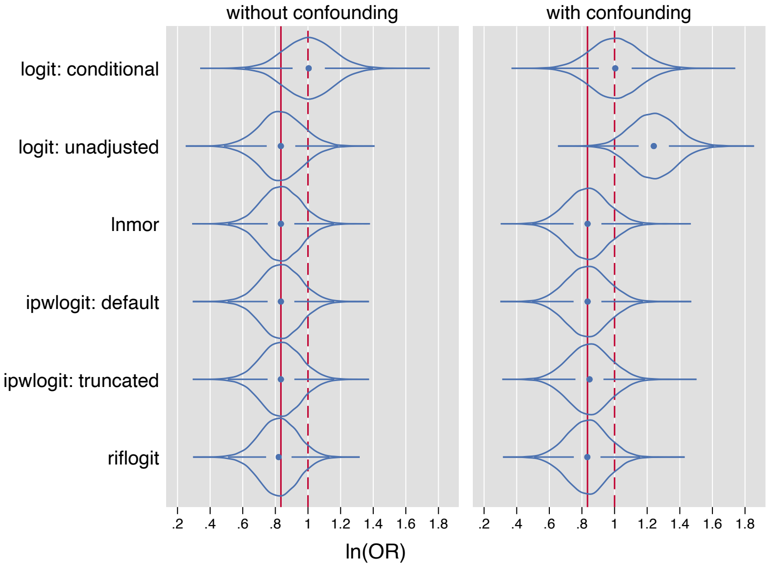
Appendix: Some simulation results

- Setup
  - Binary outcome Y depends on treatment T and control variable X through a logistic model.
  - The effects of T and X on Y (the conditional log odds ratios) are set to 1 in all simulations (intercept is 0).
  - X has a standard normal distribution.
  - T is either binary or continuous.
  - Two scenarios:
    1. unconfounded: T is independent from X (X has an even distribution if binary and a standard normal distribution if continuous)
    2. confounded: T depends on X (binary: logistic model with slope 0.5; continuous: linear model with slope 0.5 and standard normal errors)
  - 10'000 replications.
  - Using `violinplot` (Jann 2022) to display results.

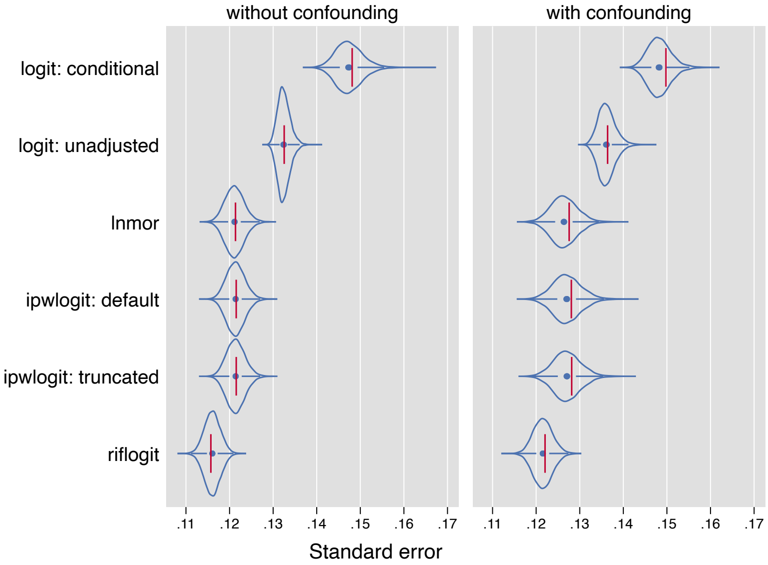
Appendix: Some simulation results

- Distribution of effect estimates for binary treatment



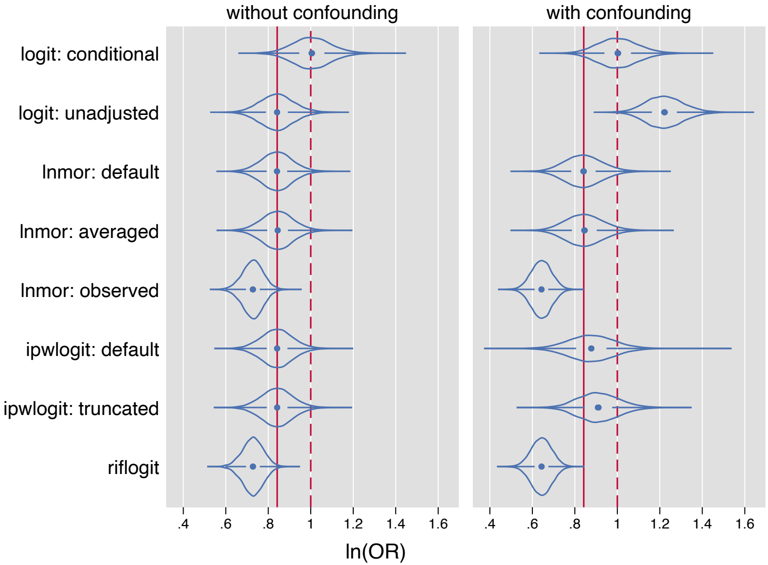
Appendix: Some simulation results

- Distribution of standard errors for binary treatment



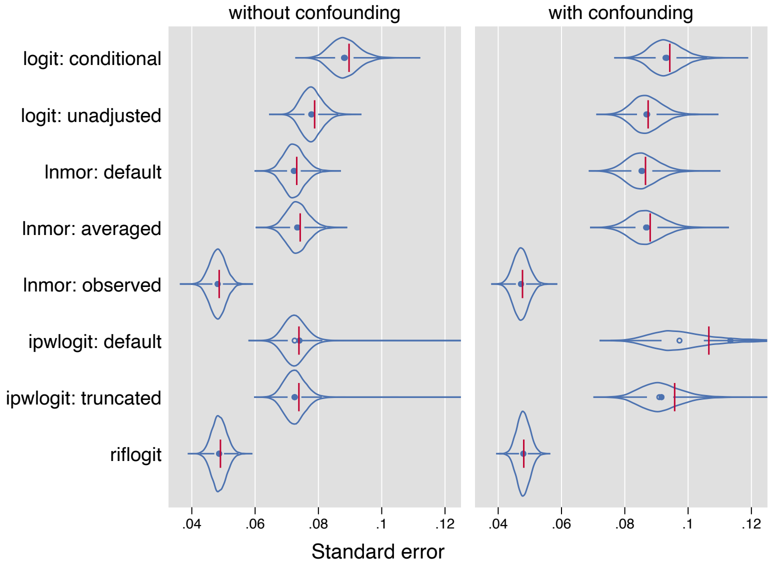
Appendix: Some simulation results

- Distribution of effect estimates for continuous treatment



Appendix: Some simulation results

- Distribution of standard errors for continuous treatment



Appendix: Some simulation results

- Binary treatment:
  - All estimators appear to work well.
  - However, note that the treatment has an even distribution in these simulations; may need to do more simulations with uneven distributions.
- Continuous treatment:
  - IPW does not fully remove confounding. Furthermore, stability of IPW becomes problematic. Truncation helps somewhat but also increases bias.
  - MOR' ("observed") is a different estimand than $\overline{\text{MOR}}$ ("averaged"). RIF logit appears to approximate MOR', not $\overline{\text{MOR}}$.

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