Marginal/conditional estimands and the issue of (non)collapsibility

Rhian Daniel, Cardiff University
PSI Webinar on Covariate Adjustment
1st December 2022

Outline

1. Re-cap elements of previous talks
2. (Non)collapsibility
3. The choice between marginal and conditional estimands
4. For more...

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  - This is the case for binary and survival outcomes, not just for continuous outcomes, contrary to some discussions.
  - Confusion enters when people compare the SE of an (adjusted) estimator of a conditional estimand with the SE of an unadjusted estimator of a marginal estimand: apple vs. orange.

Heterogeneity and (non)collapsibility

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- Depending on f, α_1 and β_1 may or may not be equal: (non)collapsibility.

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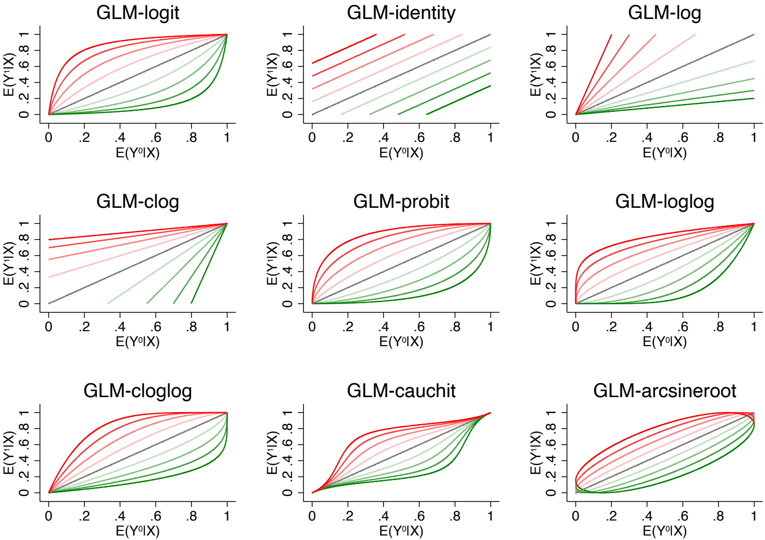
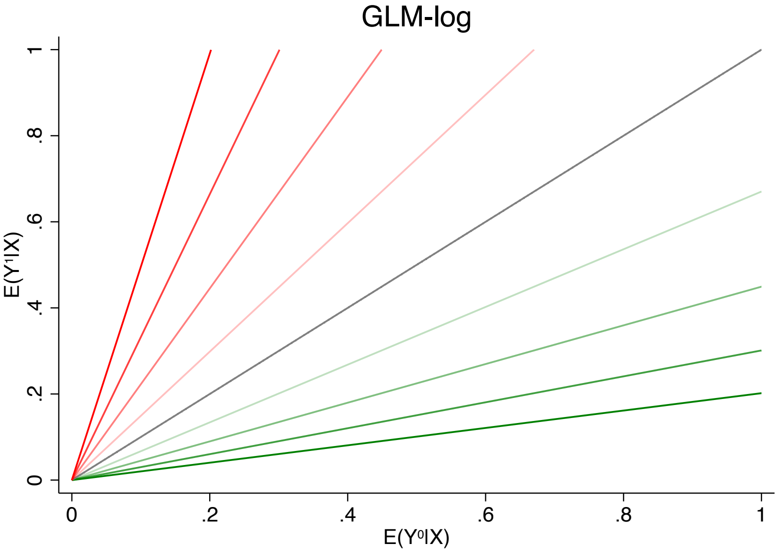
- Thus **IF** $g_{\cdot}(p)$ is a linear function of p then $\alpha_1 = \beta_1$.
- But for many link functions f, e.g. logit, $g_{\cdot}(p)$ is non-linear.

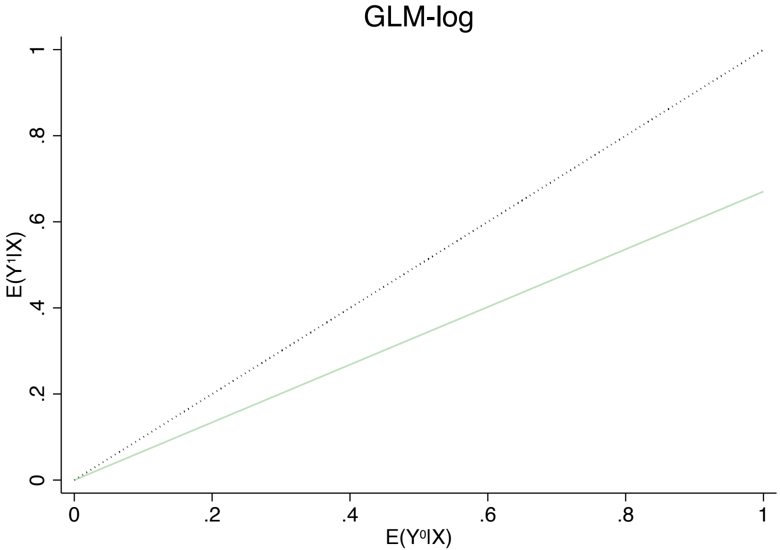
$g_{\cdot}(p)$ for common link functions



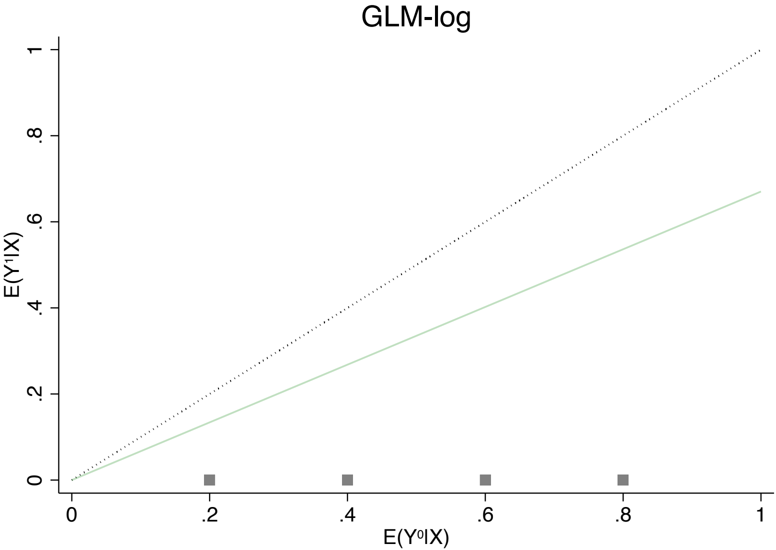
A closer look at the log link



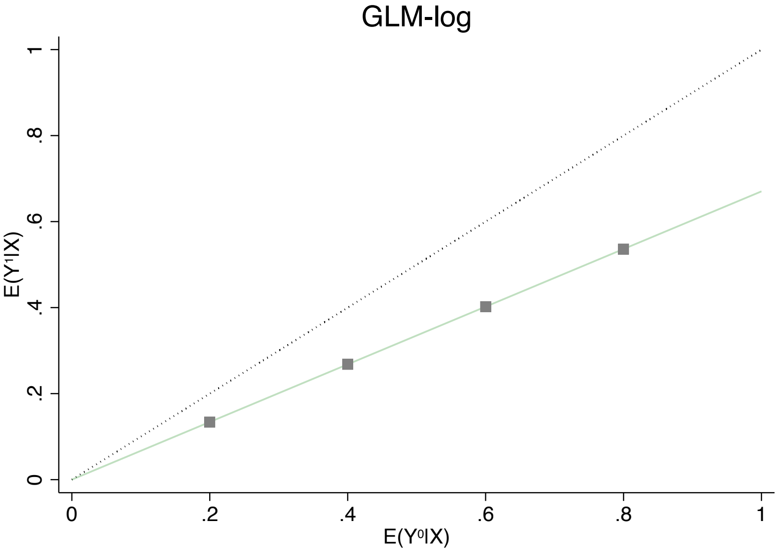
Suppose no heterogeneity and $\beta_1 = -0.4$



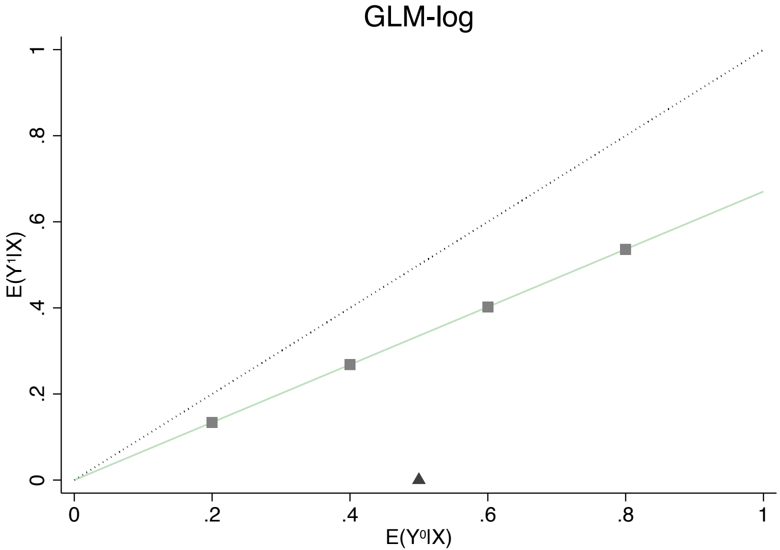
Suppose 4 (equiprobable) values of $\mathbb{E}(Y^0|X)$

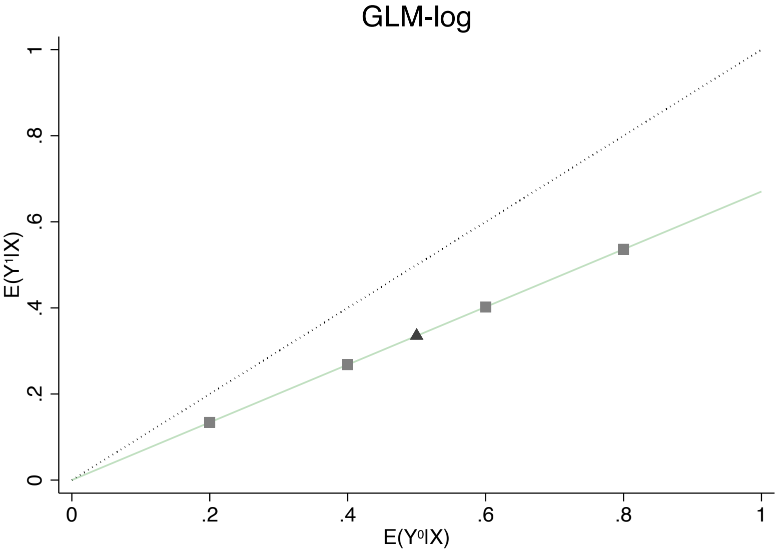


These map like this

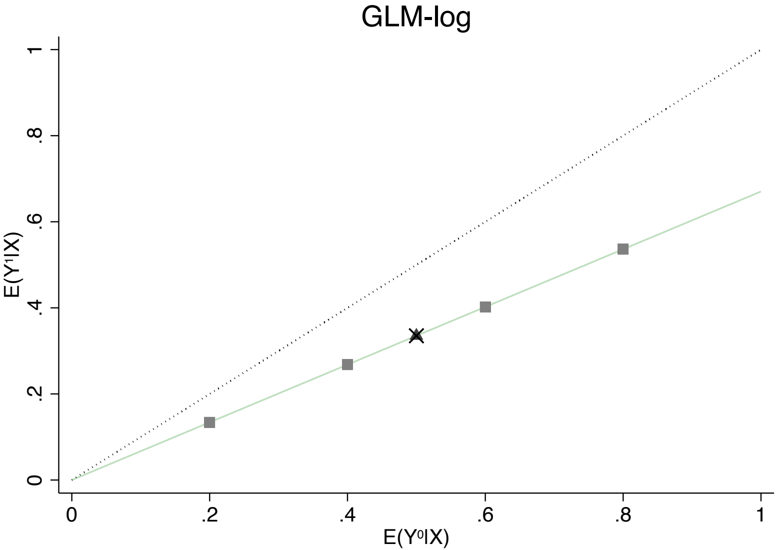


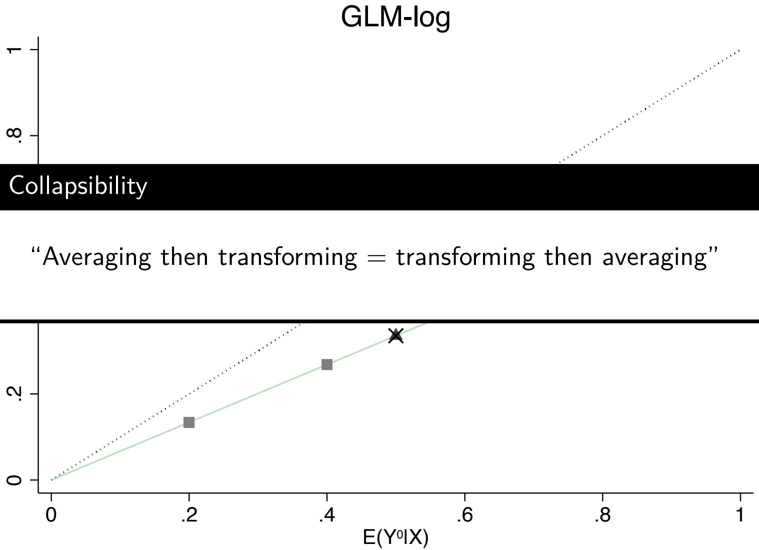
And the ('horizontal') average $\mathbb{E}(Y^0)$...




GLM-log
E(Y¹|X)
0
.2
.4
.6
.8
1
E(Y⁰|X)

. . . which is the 'vertical average', $\mathbb{E}(Y^1)$

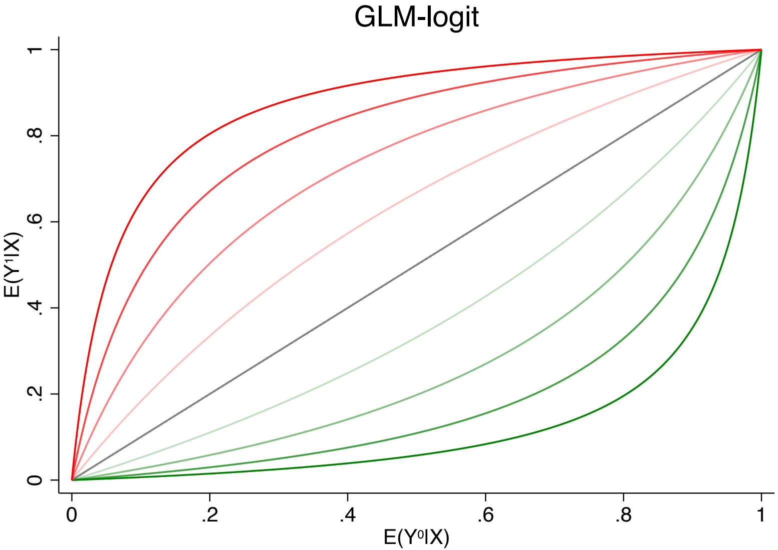




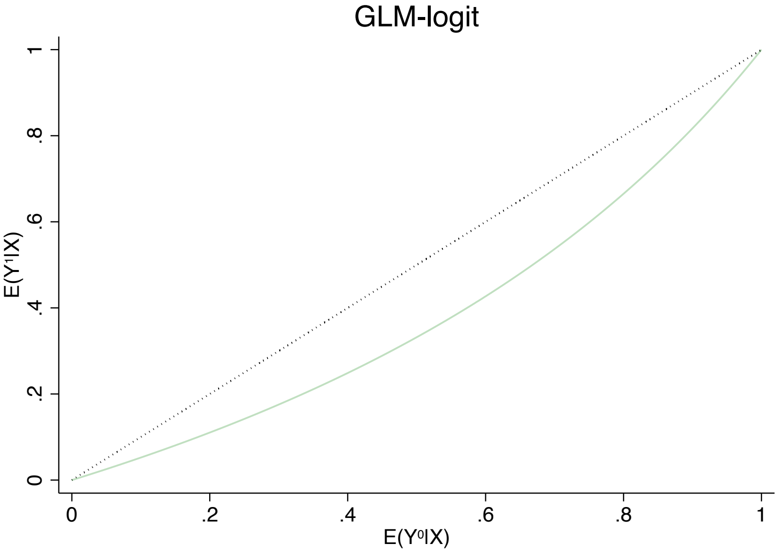
Collapsibility

"Averaging then transforming = transforming then averaging"

Now take the logit link



Suppose no heterogeneity and $\beta_1 = -0.7$



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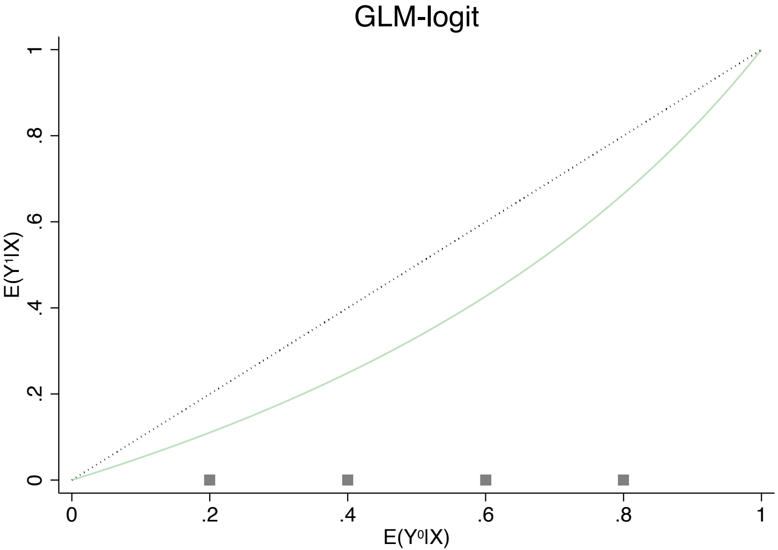

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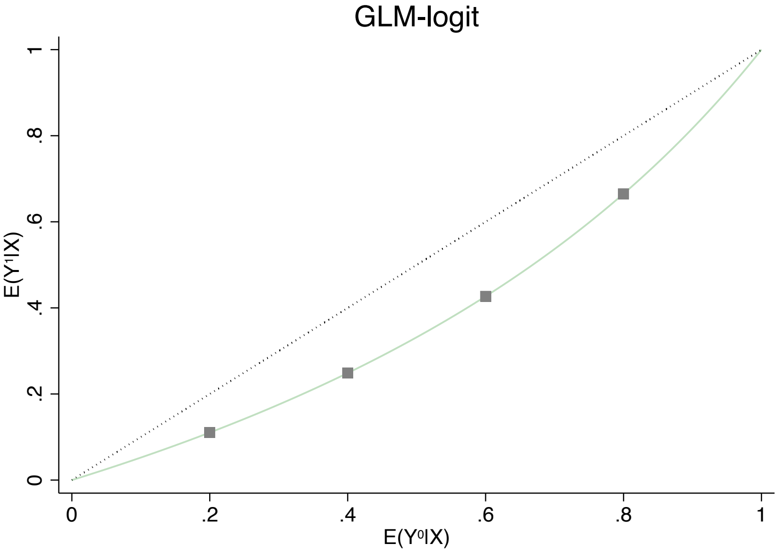

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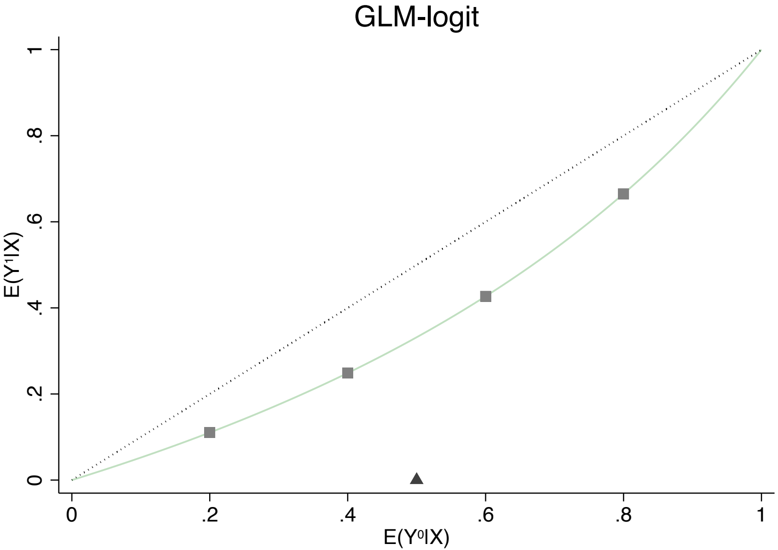

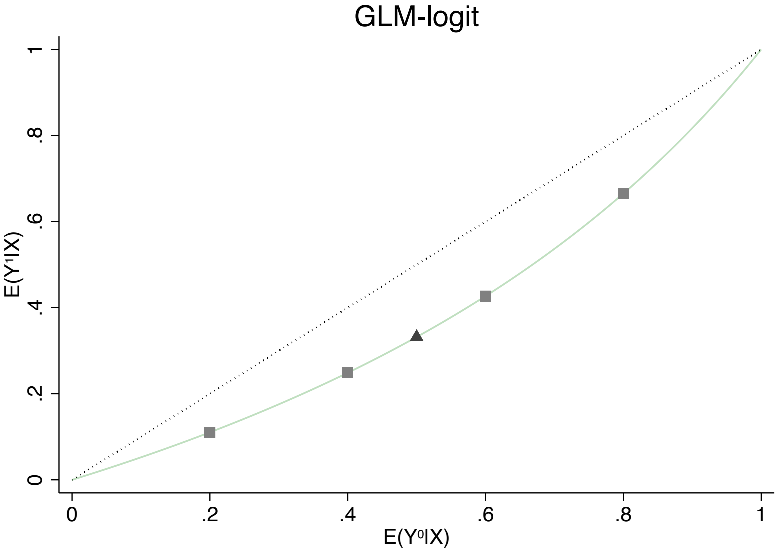
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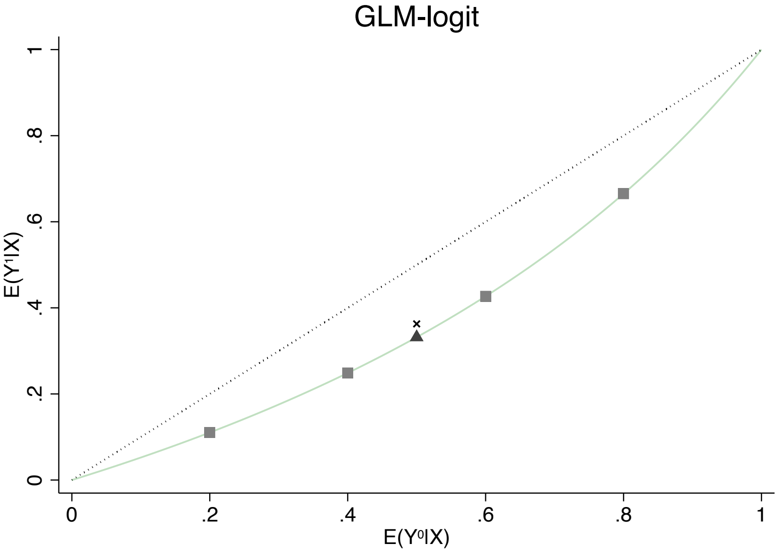

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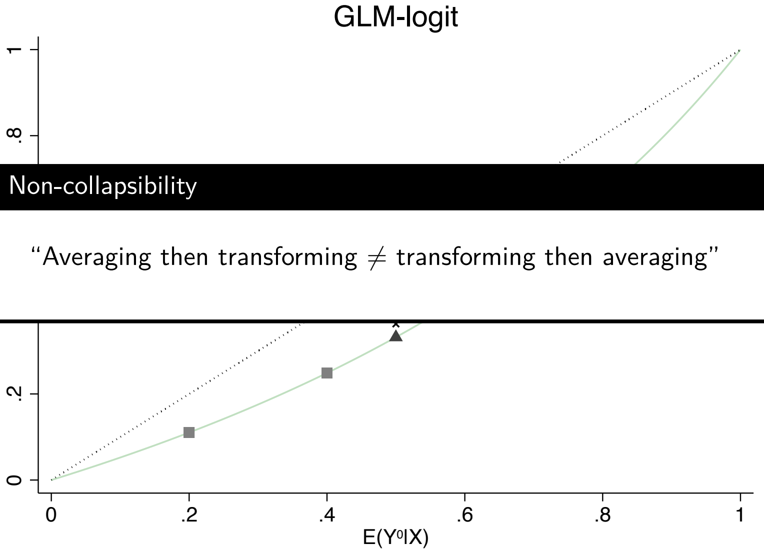

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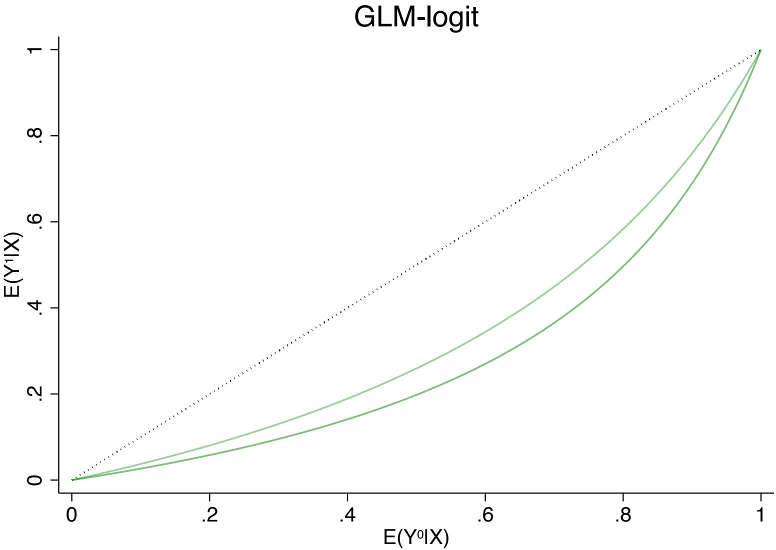

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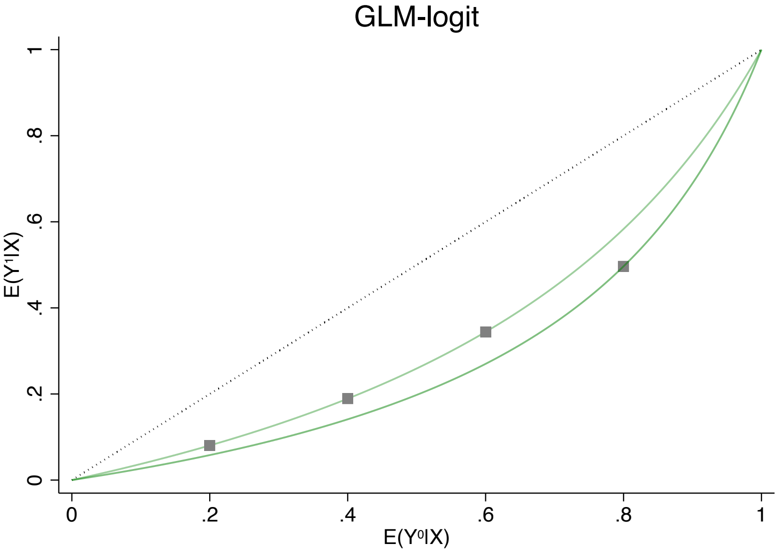

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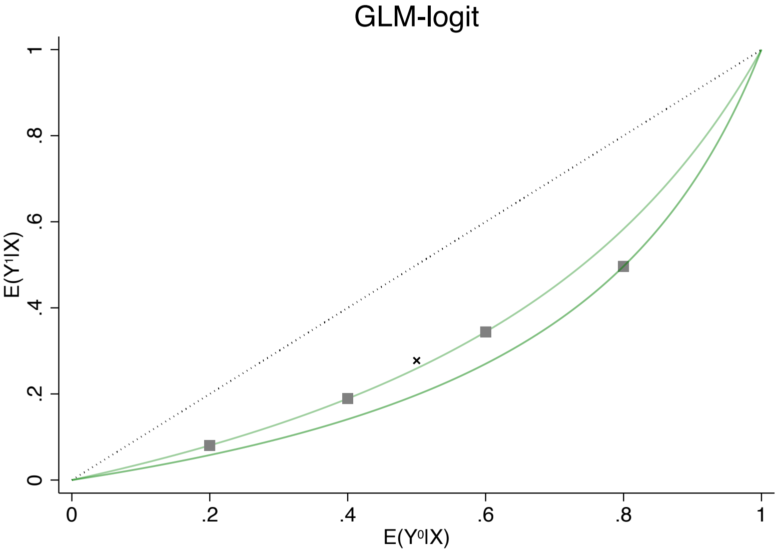

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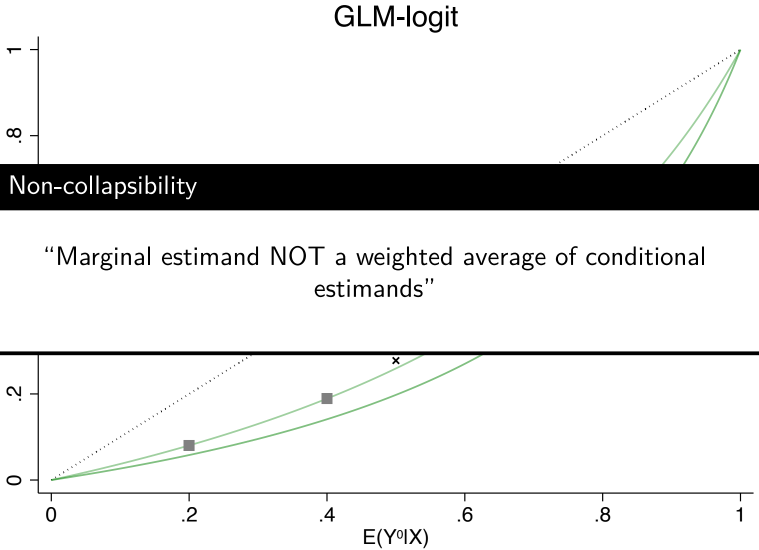

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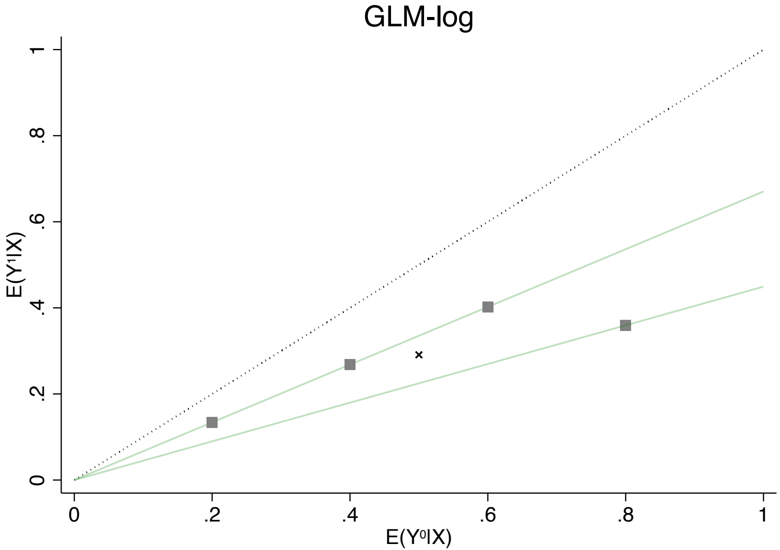

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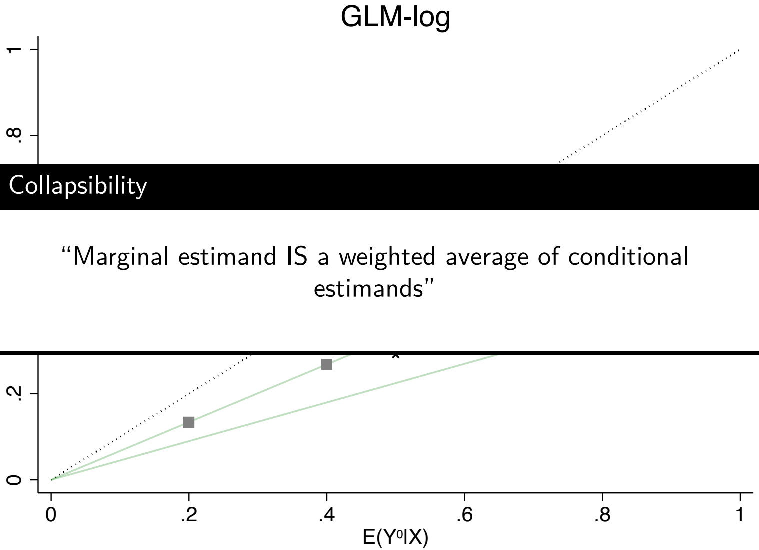

Collapsibility

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  - Tempting to think that we can apply the estimated odds ratios of 0.6 and 0.8 to this 0.2 to bound $\mathbb{E}(Y^1|\text{age, sex, comorbidities})$, but we can't because of non-collapsibility.

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  - Tempting to think that we can apply the estimated odds ratios of 0.6 and 0.8 to this 0.2 to bound $\mathbb{E}(Y^1|\text{age, sex, comorbidities})$, but we can't because of non-collapsibility.
- **The issue is not specific to binary outcomes**

Three more remarks about (non)collapsibility

- **It's not just about conditional vs. marginal**
  - If non-collapsible, every estimand conditional on different sets of X's can each be different, and each different from the marginal.
- **Consequences for counterfactual risk prediction**
  - Suppose a published study estimand is conditional on age, sex, comorbidities, genotype.
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- **The issue is not specific to binary outcomes**
  - e.g. hazard ratios in Cox PH models are non-collapsible

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2. (Non)collapsibility
3. The choice between marginal and conditional estimands
4. For more. . .

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  - Possibly, but pre-specification is possible even when using X: as discussed by Florian.

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  - See work by Anders Huitfeldt.

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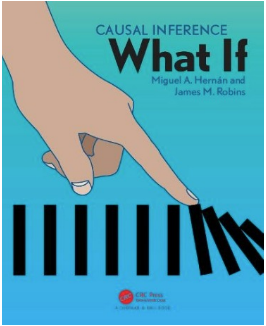
More on (non)collapsibility



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Noncollapsibility, confounding, and sparse-data bias. Part 1: The oddities of odds

Sander Greenland

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Noncollapsibility, confounding, and sparse-data bias. Part 2: What should researchers make of persistent controversies about the odds ratio?

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Huitfeldt *et al. Emerg Themes Epidemiol* (2019) 16:1
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Emerging Themes in Epidemiology

RESEARCH ARTICLE — Open Access

On the collapsibility of measures of effect in the counterfactual causal framework

Anders Huitfeldt[1*], Mats J. Stensrud[2,4] and Etsuji Suzuki[3,4]

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Biometrical Journal

RESEARCH PAPER

Making apples from oranges: Comparing noncollapsible effect estimators and their standard errors after adjustment for different covariate sets

Rhian Daniel | Jingjing Zhang | Daniel Farewell