Multiple-response models for multivariate binary response

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OUTLINE

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani

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  - Household size

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  - Wealth index

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- Response(s): Three WASH variables were created as per WHO definition
  - Drinking water source
  - Toilet facility type
  - Garbage disposal method

Objective

The aim is to investigate the contribution of demographic, socialland economic factors to improved waster, sanitation and hygien (WASH) among the urban poor.

Problems

How do we account for the repeated measurements within the households across the years?

- Model the wash variables separately (Manuscript already submitted?)

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- Pick one of the WASH indicator and treat the remaining two as fixed covariates

The two approaches are not accounting for the unmeasured variations and correlation among the WASH variables

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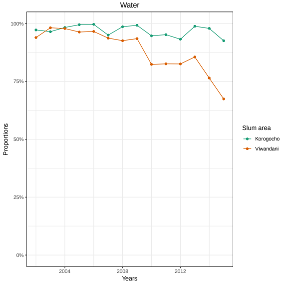

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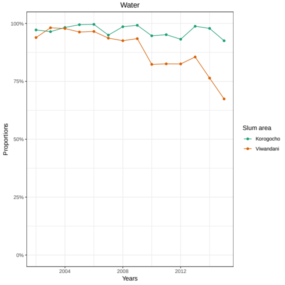

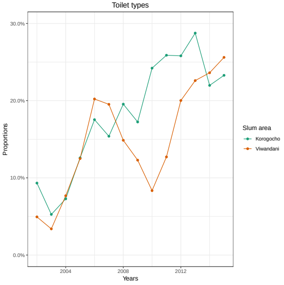

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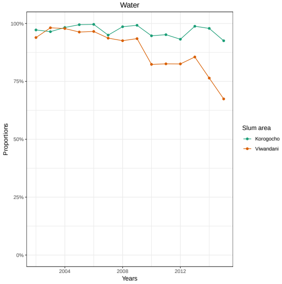

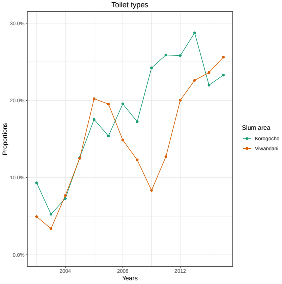

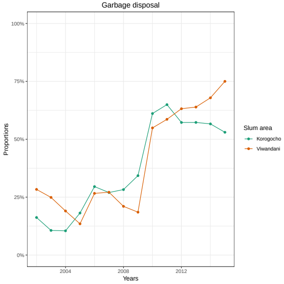

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What we may know?

- This is a difficult problem!!!

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- But we need some understanding of data generation process
    - Some simulations

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$$\hat{y}_i = U_i + \beta_{0i} + \beta_{1i}x$$

Where $i \in \{\text{WASH}\}$

- Let P be the probability that HH has access to $i \in \{\text{WASH}\}$

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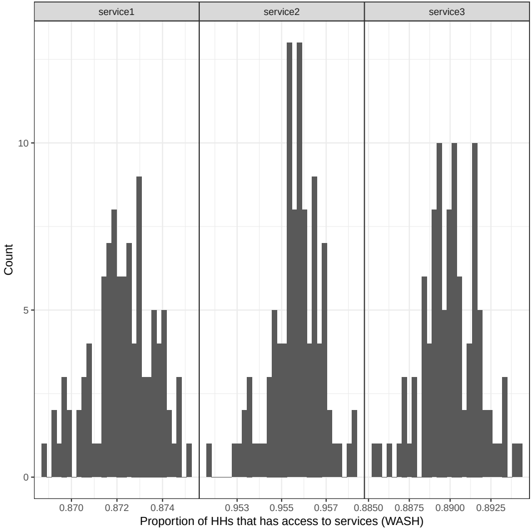
Now that we know the observed βs, can we find a model which gives us back the βs having answered the 3 question above?

Simulation results



Data structure

- Stacked response variables column-wise and predictor variables duplicated

hhid_anon	wealthindex	U	service1	service2	service3
0000E80F-FD5C-4FEF-BF10-9B54AD51A0E2	2.655956745	1.723123e-02	1	1	1
00042B8C-1DF8-48EF-886A-185A0AB70729	0.757750928	1.167529e+00	1	1	1
0004BA55-669A-4995-95D5-D9EE75E45F17	1.134567142	3.027808e-01	1	1	1
00061CB0-76E0-4981-B737-88DF822D26FD	1.832620502	1.011865e+00	1	1	1
00089D9D-39CF-450E-9CB4-A2002713AB6F	3.200252771	1.860632e-01	1	1	1
000A53A7-1054-4B2F-9E09-E29F164445A2	2.238202333	1.537059e-01	1	1	1
000BAB2C-2688-4CA7-A001-090173593622	-1.060479641	1.242479e-02	0	1	0

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hhid_anon	wealthindex	service	status
09D0CF12-E6F8-4E85-90AC-8AF0FC9F253F	2.4543889	service1	1
50849E44-B9BD-49D5-8093-E43327ACED39	-1.5968139	service1	0
8F330DF4-72B6-4F86-9C3D-CFADB5A01FFC	0.9861318	service1	1
1572654D-4D6E-49CF-8BBD-8C4B937FCCA3	0.7724096	service2	1
3D5ED844-14B7-4268-BEDE-0DA947AF99A9	1.9034044	service2	1
3F1136A9-2D1F-43FF-A325-CDB9F3D37FB5	3.1475494	service2	1
4D610CE5-F113-4924-AD9D-6727183E4B97	1.4044546	service2	1
4EA4ECCF-E315-4312-BFB2-5A02FE9E96C4	1.2261925	service2	1
CC886B39-DCE8-4122-9510-4B20B7690127	2.9173722	service2	1
811E8AC9-677E-409A-ABC8-95270E5B6C15	2.8915195	service3	1
AB4E5789-E31D-493A-AD91-51E05745DC3F	3.3699727	service3	1
B1402027-E0AA-40C5-8998-127F351A519E	0.7724096	service3	1
F480D065-92AA-4C5B-AB4F-62474D39EAFA	0.7724096	service3	1
F870E595-676F-419C-8BC8-CC751694E77B	-0.4757498	service3	0

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8F330DF4-72B6-4F86-9C3D-CFADB5A01FFC	0.9861318	service1	1
1572654D-4D6E-49CF-8BBD-8C4B937FCCA3	0.7724096	service2	1
3D5ED844-14B7-4268-BEDE-0DA947AF99A9	1.9034044	service2	1
3F1136A9-2D1F-43FF-A325-CDB9F3D37FB5	3.1475494	service2	1
4D610CE5-F113-4924-AD9D-6727183E4B97	1.4044546	service2	1
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CC886B39-DCE8-4122-9510-4B20B7690127	2.9173722	service2	1
811E8AC9-677E-409A-ABC8-95270E5B6C15	2.8915195	service3	1
AB4E5789-E31D-493A-AD91-51E05745DC3F	3.3699727	service3	1
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  - Predictor: wealthindex

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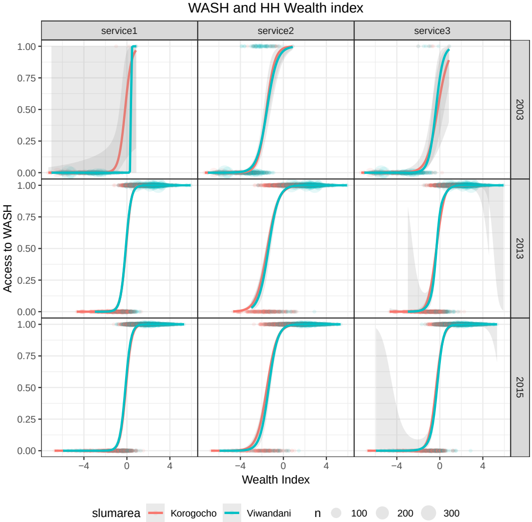

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Random effects:
 Groups    Name        Variance Std.Dev.
 hhid_anon (Intercept) 0.1498   0.3871
Number of obs: 13671, groups:  hhid_anon, 4557
Fixed effects:
                            Estimate Std. Error z value Pr(>|z|)
serviceservice1              0.38483    0.08905   4.322 1.55e-05 ***
serviceservice2              2.99555    0.14622  20.487  < 2e-16 ***
serviceservice3              1.12193    0.08834  12.700  < 2e-16 ***
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
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servicsrvc2  0.071
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wlthndx:sr1 -0.138  0.241  0.169
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Modelling

- Model 1: Different intercepts for different HH

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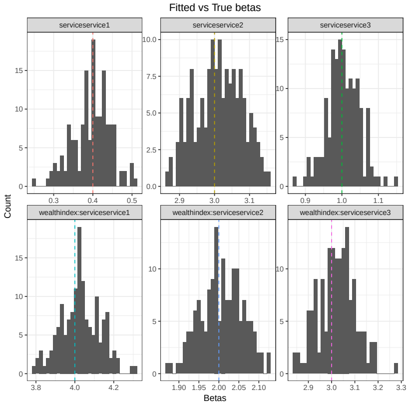

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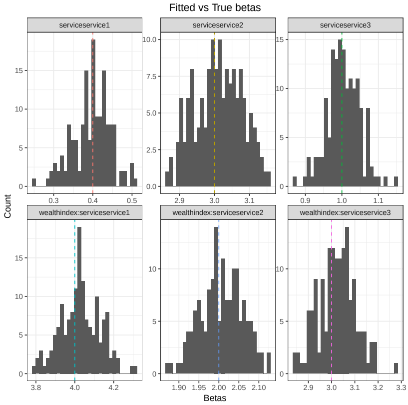

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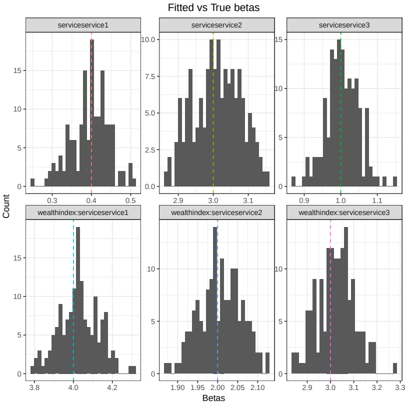

- Comments:
  - Captures *True* βs but no random slopes for services

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           serviceservice3 3535.9781 59.4641  -0.52 -0.29
Number of obs: 13443, groups:  hhid_anon, 4481
Fixed effects:
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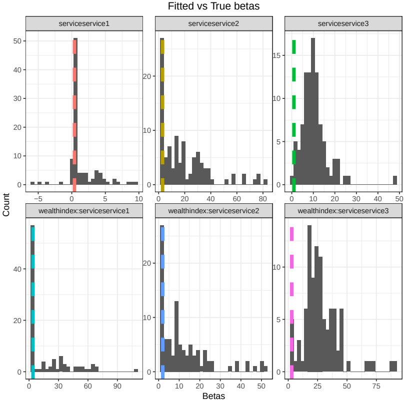

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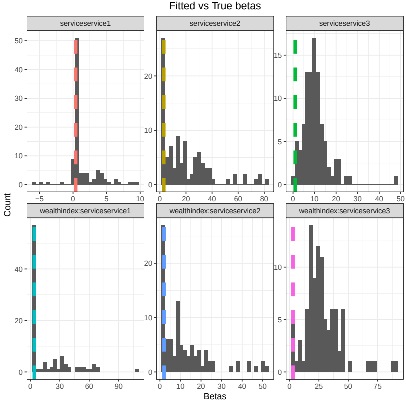

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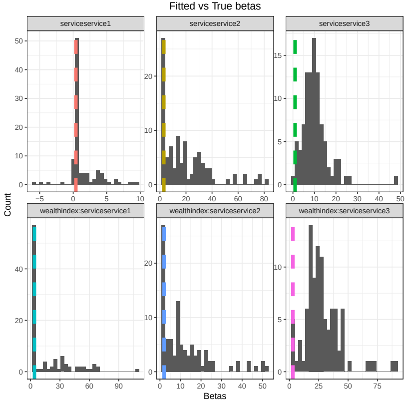

- Comments:
  - Random slopes for services but not able to capture *true* βs

New Hypothesis

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Asanteni Sana