Modeling approaches for multivariate binary response

Steve Cygu & Prof. Jonathan Dushoff
McMaster University, Canada.

Damazo Kadengye & Samuel Iddi
APHRC, Nairobi.

April 08, 2019

OUTLINE

Background

Objective

Methods

- Simulations
- Model fitting
- New Approaches

Background

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

Background

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

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
  - Slum area

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
  - Slum area
  - Interview year

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
  - Slum area
  - Interview year
  - Age

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
    - Slum area
    - Interview year
    - Age
    - Gender

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
  - Slum area
  - Interview year
  - Age
  - Gender
  - Ethnicity

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
  - Slum area
  - Interview year
  - Age
  - Gender
  - Ethnicity
  - Household size

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
  - Slum area
  - Interview year
  - Age
  - Gender
  - Ethnicity
  - Household size
  - Wealth index

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
  - Slum area
  - Interview year
  - Age
  - Gender
  - Ethnicity
  - Household size
  - Wealth index
  - Household expenditure

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
  - Slum area
  - Interview year
  - Age
  - Gender
  - Ethnicity
  - Household size
  - Wealth index
  - Household expenditure
- Response(s): Three WASH variables were created as per WHO definition

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
  - Slum area
  - Interview year
  - Age
  - Gender
  - Ethnicity
  - Household size
  - Wealth index
  - Household expenditure
- Response(s): Three WASH variables were created as per WHO definition
  - Drinking water source

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
  - Slum area
  - Interview year
  - Age
  - Gender
  - Ethnicity
  - Household size
  - Wealth index
  - Household expenditure
- Response(s): Three WASH variables were created as per WHO definition
  - Drinking water source
  - Toilet facility type

Background

- Longitudinal (2003 - 2015) NUHDSS covering Korogocho and Viwandani
- Predictors
    - Slum area
    - Interview year
    - Age
    - Gender
    - Ethnicity
    - Household size
    - Wealth index
    - Household expenditure
- 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, social and 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?)

Problems

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

- Model the wash variables separately (Manuscript already submitted?)
- Pick one of the WASH indicator and treat the remaining two as fixed covariates

Problems

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

- Model the wash variables separately (Manuscript already submitted?)
- Pick one of the WASH indicator and treat the remaining two as fixed covariates

Problems

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

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

Problems

Does this matter?

- Access to any of the WASH indicators (variables) vary within the households and also across the years.

Problems

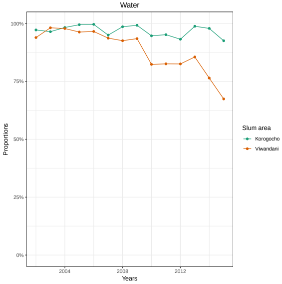
Does this matter?

- Access to any of the WASH indicators (variables) vary within the households and also across the years.

Problems

Does this matter?

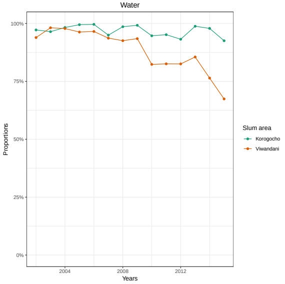
- Access to any of the WASH indicators (variables) vary within the households and also across the years.

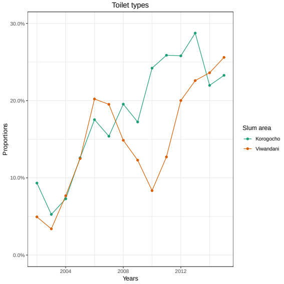


Problems

Does this matter?

- Access to any of the WASH indicators (variables) vary within the households and also across the years.

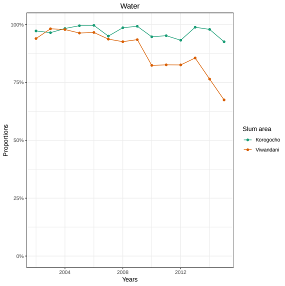


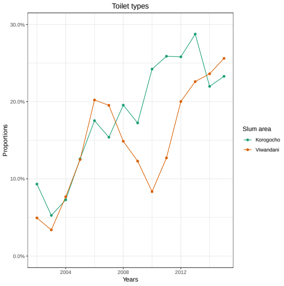


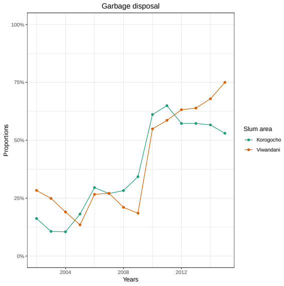
Problems

Does this matter?

- Access to any of the WASH indicators (variables) vary within the households and also across the years.







Problems

There are several questions we can ask:

1. How do we pull information from (across) the three levels (WASH)?

Problems

There are several questions we can ask:

1. How do we pull information from (across) the three levels (WASH)?
   - Can we account for household level variations?

Problems

There are several questions we can ask:

1. How do we pull information from (across) the three levels (WASH)?
    - Can we account for household level variations?
2. Can we estimate the correlation between the WASH variables while controlling for the other covariates?

Problems

There are several questions we can ask:

1. How do we pull information from (across) the three levels (WASH)?
   - Can we account for household level variations?
2. Can we estimate the correlation between the WASH variables while controlling for the other covariates?
3. Can we control for the variation and still get a reliable estimate of the covariance?

Problems

There are several questions we can ask:

1. How do we pull information from (across) the three levels (WASH)?
   - Can we account for household level variations?
2. Can we estimate the correlation between the WASH variables while controlling for the other covariates?
3. Can we control for the variation and still get a reliable estimate of the covariance?

Problems

There are several questions we can ask:

1. How do we pull information from (across) the three levels (WASH)?
   - Can we account for household level variations?
2. Can we estimate the correlation between the WASH variables while controlling for the other covariates?
3. Can we control for the variation and still get a reliable estimate of the covariance?

What we may know?

- This is a difficult problem!!!

Problems

There are several questions we can ask:

1. How do we pull information from (across) the three levels (WASH)?
    - Can we account for household level variations?
2. Can we estimate the correlation between the WASH variables while controlling for the other covariates?
3. Can we control for the variation and still get a reliable estimate of the covariance?

What we may know?

- This is a difficult problem!!!
- Generalised linear mixed effects models may be a good starting point

Problems

There are several questions we can ask:

1. How do we pull information from (across) the three levels (WASH)?
   - Can we account for household level variations?
2. Can we estimate the correlation between the WASH variables while controlling for the other covariates?
3. Can we control for the variation and still get a reliable estimate of the covariance?

What we may know?

- This is a difficult problem!!!
- Generalised linear mixed effects models may be a good starting point
- But we need some understanding of data generation process

Problems

There are several questions we can ask:

1. How do we pull information from (across) the three levels (WASH)?
    - Can we account for household level variations?
2. Can we estimate the correlation between the WASH variables while controlling for the other covariates?
3. Can we control for the variation and still get a reliable estimate of the covariance?

What we may know?

- This is a difficult problem!!!
- Generalised linear mixed effects models may be a good starting point
- But we need some understanding of data generation process
    - Some simulations

Methods

Assume that we only observed the predictors and simulate response

- Pick one of the predictors - wealth index, x

Methods

Assume that we only observed the predictors and simulate response

- Pick one of the predictors - wealth index, x
- There are some unobserved confounders, U, effect

Methods

Assume that we only observed the predictors and simulate response

- Pick one of the predictors - wealth index, x
- There are some unobserved confounders, U, effect
- Assume we know the effect sizes, βs

Methods

Assume that we only observed the predictors and simulate response

- Pick one of the predictors - wealth index, x
- There are some unobserved confounders, U, effect
- Assume we know the effect sizes, βs

Methods

Assume that we only observed the predictors and simulate response

- Pick one of the predictors - wealth index, x
- There are some unobserved confounders, U, effect
- Assume we know the effect sizes, βs

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

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

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

$$P = \frac{1}{1 + \exp\left(-\hat{y}_i\right)}$$

Methods

Assume that we only observed the predictors and simulate response

- Pick one of the predictors - wealth index, x
- There are some unobserved confounders, U, effect
- Assume we know the effect sizes, βs

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

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

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

$$P = \frac{1}{1 + \exp\left(-\hat{y}_i\right)}$$

- Simulate response, y_i from a binomial distribution with probability of observing WASH P

Methods

Assume that we only observed the predictors and simulate response

- Pick one of the predictors - wealth index, x
- There are some unobserved confounders, U, effect
- Assume we know the effect sizes, βs

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

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

$$P = \frac{1}{1 + \exp\left(-\hat{y}_i\right)}$$

- Simulate response, y_i from a binomial distribution with probability of observing WASH P

Methods

Assume that we only observed the predictors and simulate response

- Pick one of the predictors - wealth index, x
- There are some unobserved confounders, U, effect
- Assume we know the effect sizes, βs

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

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

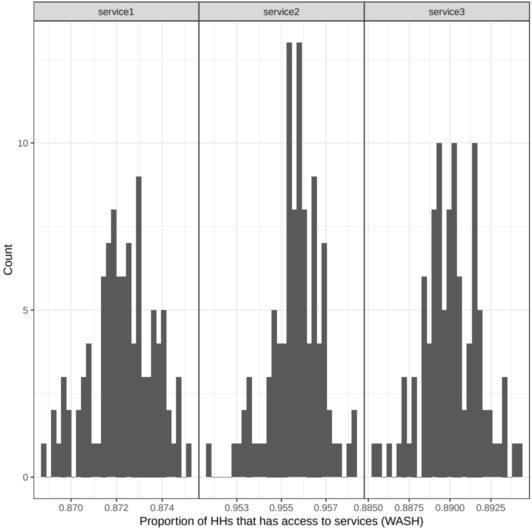
- Let P be the probability that HH has access to $i \in \{\text{WASH}\}$

$$P = \frac{1}{1 + \exp\left(-\hat{y}_i\right)}$$

- Simulate response, y_i from a binomial distribution with probability of observing WASH P

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

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

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

$\Longrightarrow$

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

$\Longrightarrow$

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

- The idea is to fit a Generalized Linear Mixed-Effects Model with varying intercepts for the services

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

$\Longrightarrow$

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

- The idea is to fit a Generalized Linear Mixed-Effects Model with varying intercepts for the services
  - New response: status

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

$\Longrightarrow$

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

- The idea is to fit a Generalized Linear Mixed-Effects Model with varying intercepts for the services
    - New response: status
    - Predictor: wealthindex

Data structure

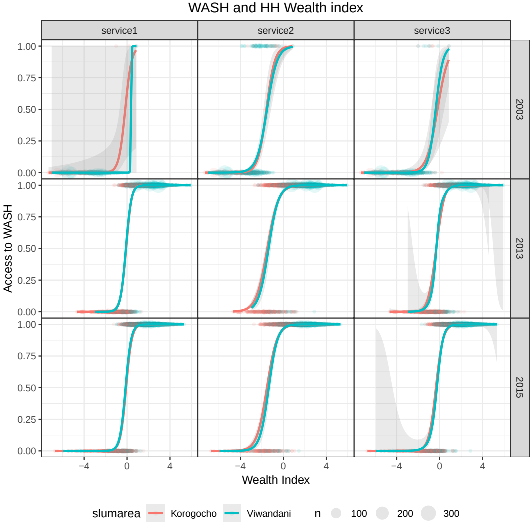
- So many things to take into account even with this simple simulation!

Data structure

- So many things to take into account even with this simple simulation!

Data structure

- So many things to take into account even with this simple simulation!



Modelling

- Model 1: Different intercepts for different HH

Modelling

- Model 1: Different intercepts for different HH

```
model <- glmer(status ~ 0 + wealthindex:service + service
   + (1|hhid_anon))
   , data = data
   , family = binomial
)
```

Modelling

- Model 1: Different intercepts for different HH

```
model <- glmer(status ~ 0 + wealthindex:service + service
   + (1|hhid_anon))
   , data = data
   , family = binomial
)
```

Modelling

- Model 1: Different intercepts for different HH

```
model <- glmer(status ~ 0 + wealthindex:service + service
    + (1|hhid_anon))
    , data = data
    , family = binomial
)
```

Modelling

- Model 1: Different intercepts for different HH

```
model <- glmer(status ~ 0 + wealthindex:service + service
   + (1|hhid_anon))
   , data = data
   , family = binomial
)
```

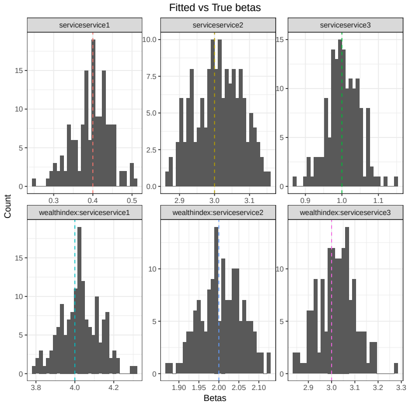
```
Random effects:
 Groups    Name        Variance Std.Dev.
 hhid_anon (Intercept) 0.1498   0.3871
Number of obs: 13671, groups:  hhid_anon, 4557
Fixed effects:
                            Estimate Std. Error z value Pr(>|z|)
serviceservice1              0.38483    0.08905   4.322 1.55e-05 ***
serviceservice2              2.99555    0.14622  20.487  < 2e-16 ***
serviceservice3              1.12193    0.08834  12.700  < 2e-16 ***
wealthindex:serviceservice1  3.98509    0.21353  18.663  < 2e-16 ***
wealthindex:serviceservice2  2.08893    0.11548  18.089  < 2e-16 ***
wealthindex:serviceservice3  3.01912    0.15519  19.454  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:
            srvcs1 srvcs2 srvcs3 wlth:1 wlth:2
servicsrvc2  0.071
servicsrvc3  0.065  0.177
wlthndx:sr1 -0.138  0.241  0.169
wlthndx:sr2  0.055  0.693  0.139  0.199
```

Modelling

- Model 1: Different intercepts for different HH

```
model <- glmer(status ~ 0 + wealthindex:service + service
    + (1|hhid_anon))
    , data = data
    , family = binomial
)
```

```
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 ***
wealthindex:serviceservice1 3.98509    0.21353  18.663  < 2e-16 ***
wealthindex:serviceservice2 2.08893    0.11548  18.089  < 2e-16 ***
wealthindex:serviceservice3 3.01912    0.15519  19.454  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:
            srvcs1 srvcs2 srvcs3 wlth:1 wlth:2
servicsrvc2  0.071
servicsrvc3  0.065  0.177
wlthndx:sr1 -0.138  0.241  0.169
wlthndx:sr2  0.055  0.693  0.139  0.199
```

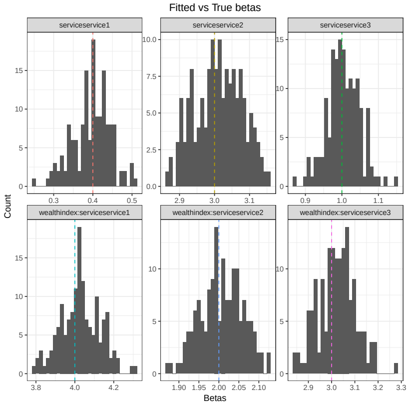


Modelling

- Model 1: Different intercepts for different HH

```
model <- glmer(status ~ 0 + wealthindex:service + service
    + (1|hhid_anon))
    , data = data
    , family = binomial
)
```

```
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 ***
wealthindex:serviceservice1  3.98509    0.21353  18.663  < 2e-16 ***
wealthindex:serviceservice2  2.08893    0.11548  18.089  < 2e-16 ***
wealthindex:serviceservice3  3.01912    0.15519  19.454  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:
            srvcs1 srvcs2 srvcs3 wlth:1 wlth:2
servicsrvc2  0.071
servicsrvc3  0.065  0.177
wlthndx:sr1 -0.138  0.241  0.169
wlthndx:sr2  0.055  0.693  0.139  0.199
```



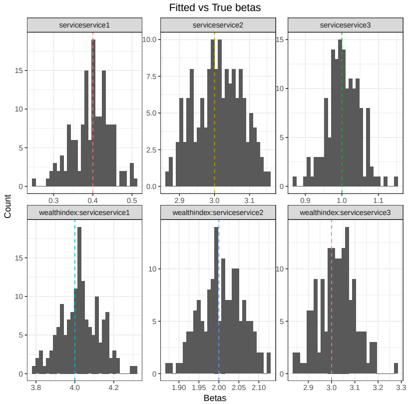
- Comments:

Modelling

- Model 1: Different intercepts for different HH

```
model <- glmer(status ~ 0 + wealthindex:service + service
    + (1|hhid_anon))
    , data = data
    , family = binomial
)
```

```
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 ***
wealthindex:serviceservice1  3.98509    0.21353  18.663  < 2e-16 ***
wealthindex:serviceservice2  2.08893    0.11548  18.089  < 2e-16 ***
wealthindex:serviceservice3  3.01912    0.15519  19.454  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:
            srvcs1 srvcs2 srvcs3 wlth:1 wlth:2
servicsrvc2  0.071
servicsrvc3  0.065  0.177
wlthndx:sr1 -0.138  0.241  0.169
wlthndx:sr2  0.055  0.693  0.139  0.199
```



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

- Model 2: Different intercepts for different HH and random slopes for services

- Model 2: Different intercepts for different HH and random slopes for services

```
model <- glmer(status ~ 0 + wealthindex:service + service
   + (service + 0|hhid_anon))
   , data = data
   , family = binomial
)
```

- Model 2: Different intercepts for different HH and random slopes for services

```
model <- glmer(status ~ 0 + wealthindex:service + service
   + (service + 0|hhid_anon))
   , data = data
   , family = binomial
)
```

- Model 2: Different intercepts for different HH and random slopes for services

```
model <- glmer(status ~ 0 + wealthindex:service + service
   + (service + 0|hhid_anon))
   , data = data
   , family = binomial
)
```

- Model 2: Different intercepts for different HH and random slopes for services

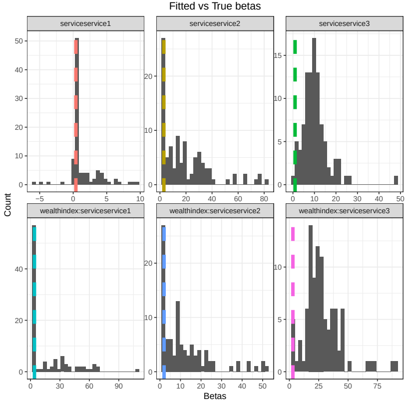
```
model <- glmer(status ~ 0 + wealthindex:service + service
    + (service + 0|hhid_anon))
    , data = data
    , family = binomial
)
```

```
Random effects:
 Groups    Name            Variance  Std.Dev. Corr
 hhid_anon serviceservice1 1100.9631 33.1808
           serviceservice2    0.1178  0.3432  -0.67
           serviceservice3 3535.9781 59.4641  -0.52 -0.29
Number of obs: 13443, groups:  hhid_anon, 4481
Fixed effects:
                             Estimate Std. Error z value Pr(>|z|)
serviceservice1             4.661e+00  5.294e-04    8803   <2e-16 ***
serviceservice2             2.880e+00  4.940e-04    5830   <2e-16 ***
serviceservice3             1.245e+01  5.313e-04   23429   <2e-16 ***
wealthindex:serviceservice1 3.017e+01  4.996e-04   60387   <2e-16 ***
wealthindex:serviceservice2 1.810e+00  4.875e-04    3714   <2e-16 ***
wealthindex:serviceservice3 3.471e+01  5.031e-04   68990   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:
            srvcs1 srvcs2 srvcs3 wlth:1 wlth:2
servicsrvc2 0.018
servicsrvc3 0.077  0.027
wlthndx:sr1 0.022  0.025  0.041
wlthndx:sr2 0.008  0.011  0.012  0.011
wlthndx:sr3 0.035  0.027  0.046  0.041  0.012
```

- Model 2: Different intercepts for different HH and random slopes for services

```
model <- glmer(status ~ 0 + wealthindex:service + service
    + (service + 0|hhid_anon))
    , data = data
    , family = binomial
)
```

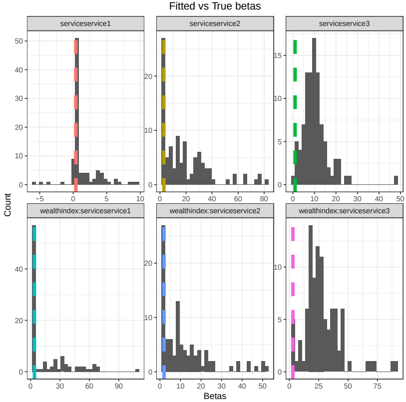
```
Random effects:
 Groups    Name            Variance  Std.Dev. Corr
 hhid_anon serviceservice1 1100.9631 33.1808
           serviceservice2    0.1178  0.3432  -0.67
           serviceservice3 3535.9781 59.4641  -0.52 -0.29
Number of obs: 13443, groups:  hhid_anon, 4481
Fixed effects:
                            Estimate Std. Error z value Pr(>|z|)
serviceservice1            4.661e+00  5.294e-04    8803   <2e-16 ***
serviceservice2            2.880e+00  4.940e-04    5830   <2e-16 ***
serviceservice3            1.245e+01  5.313e-04   23429   <2e-16 ***
wealthindex:serviceservice1 3.017e+01  4.996e-04   60387   <2e-16 ***
wealthindex:serviceservice2 1.810e+00  4.875e-04    3714   <2e-16 ***
wealthindex:serviceservice3 3.471e+01  5.031e-04   68990   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:
            srvcs1 srvcs2 srvcs3 wlth:1 wlth:2
servicsrvc2 0.018
servicsrvc3 0.077  0.027
wlthndx:sr1 0.022  0.025  0.041
wlthndx:sr2 0.008  0.011  0.012  0.011
wlthndx:sr3 0.035  0.027  0.046  0.041  0.012
```



- Model 2: Different intercepts for different HH and random slopes for services

```
model <- glmer(status ~ 0 + wealthindex:service + service
    + (service + 0|hhid_anon))
    , data = data
    , family = binomial
)
```

```
Random effects:
 Groups    Name            Variance  Std.Dev. Corr
 hhid_anon serviceservice1 1100.9631 33.1808
           serviceservice2    0.1178  0.3432  -0.67
           serviceservice3 3535.9781 59.4641  -0.52 -0.29
Number of obs: 13443, groups:  hhid_anon, 4481
Fixed effects:
                            Estimate Std. Error z value Pr(>|z|)
serviceservice1            4.661e+00  5.294e-04    8803   <2e-16 ***
serviceservice2            2.880e+00  4.940e-04    5830   <2e-16 ***
serviceservice3            1.245e+01  5.313e-04   23429   <2e-16 ***
wealthindex:serviceservice1 3.017e+01  4.996e-04   60387   <2e-16 ***
wealthindex:serviceservice2 1.810e+00  4.875e-04    3714   <2e-16 ***
wealthindex:serviceservice3 3.471e+01  5.031e-04   68990   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:
            srvcs1 srvcs2 srvcs3 wlth:1 wlth:2
servicsrvc2 0.018
servicsrvc3 0.077  0.027
wlthndx:sr1 0.022  0.025  0.041
wlthndx:sr2 0.008  0.011  0.012  0.011
wlthndx:sr3 0.035  0.027  0.046  0.041  0.012
```

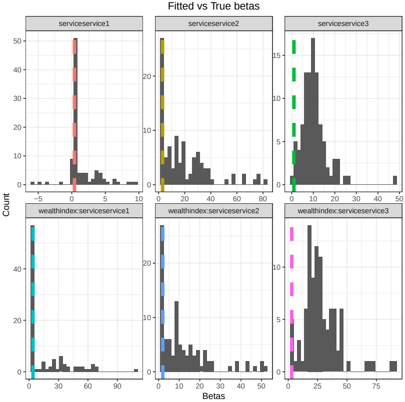


- Comments:

- Model 2: Different intercepts for different HH and random slopes for services

```
model <- glmer(status ~ 0 + wealthindex:service + service
    + (service + 0|hhid_anon))
    , data = data
    , family = binomial
)
```

```
Random effects:
 Groups    Name            Variance  Std.Dev. Corr
 hhid_anon serviceservice1 1100.9631 33.1808
           serviceservice2    0.1178  0.3432  -0.67
           serviceservice3 3535.9781 59.4641  -0.52 -0.29
Number of obs: 13443, groups:  hhid_anon, 4481
Fixed effects:
                            Estimate Std. Error z value Pr(>|z|)
serviceservice1            4.661e+00  5.294e-04    8803   <2e-16 ***
serviceservice2            2.880e+00  4.940e-04    5830   <2e-16 ***
serviceservice3            1.245e+01  5.313e-04   23429   <2e-16 ***
wealthindex:serviceservice1 3.017e+01  4.996e-04   60387   <2e-16 ***
wealthindex:serviceservice2 1.810e+00  4.875e-04    3714   <2e-16 ***
wealthindex:serviceservice3 3.471e+01  5.031e-04   68990   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Correlation of Fixed Effects:
            srvcs1 srvcs2 srvcs3 wlth:1 wlth:2
servicsrvc2 0.018
servicsrvc3 0.077  0.027
wlthndx:sr1 0.022  0.025  0.041
wlthndx:sr2 0.008  0.011  0.012  0.011
wlthndx:sr3 0.035  0.027  0.046  0.041  0.012
```



- Comments:
  - Random slopes for services but not sure of *true* βs

New Approaches

- Discussed the results with Mac-Theobio Lab

New Approaches

- Discussed the results with Mac-Theobio Lab
  - Unidentifiability of latent variability in binary-response models

New Approaches

- Discussed the results with Mac-Theobio Lab
  - Unidentifiability of latent variability in binary-response models
  - Moving to Markov chain Monte Carlo Sampler for Multivariate Generalised Linear Mixed Models

Asanteni Sana