

Det_adol_fertility

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##Loading Data

```
bdhs <- read_sav("adolescent fertility new.SAV")
bdhs
```

```
## # A tibble: 2,449 x 17
##   V013      V024      V025      V106      V130      V151      V701      WomenEmpowerment
##   <dbl+lbl> <dbl+lbl> <dbl+lbl> <dbl+lbl> <dbl+lbl> <dbl+lbl> <dbl+lbl> <dbl+lbl>
## 1 1 [15-19] 1 [Barish~ 1 [Urb~ 2 [Sec~ 1 [Mus~ 1 [Mal~ 2 [Sec~ 1 [No]
## 2 1 [15-19] 1 [Barish~ 1 [Urb~ 2 [Sec~ 1 [Mus~ 1 [Mal~ 2 [Sec~ 1 [No]
## 3 1 [15-19] 1 [Barish~ 1 [Urb~ 1 [Pri~ 1 [Mus~ 2 [Fem~ 2 [Sec~ 1 [No]
## 4 1 [15-19] 1 [Barish~ 1 [Urb~ 2 [Sec~ 1 [Mus~ 1 [Mal~ 2 [Sec~ 1 [No]
## 5 1 [15-19] 1 [Barish~ 1 [Urb~ 1 [Pri~ 1 [Mus~ 1 [Mal~ 0 [No ~ 0 [Empowered]
## 6 1 [15-19] 1 [Barish~ 1 [Urb~ 0 [No ~ 1 [Mus~ 2 [Fem~ 1 [Pri~ 0 [Empowered]
## 7 1 [15-19] 1 [Barish~ 1 [Urb~ 2 [Sec~ 1 [Mus~ 1 [Mal~ 2 [Sec~ 1 [No]
## 8 1 [15-19] 1 [Barish~ 1 [Urb~ 2 [Sec~ 1 [Mus~ 1 [Mal~ 0 [No ~ 0 [Empowered]
## 9 1 [15-19] 1 [Barish~ 1 [Urb~ 2 [Sec~ 1 [Mus~ 1 [Mal~ 2 [Sec~ 1 [No]
## 10 1 [15-19] 1 [Barish~ 1 [Urb~ 2 [Sec~ 1 [Mus~ 1 [Mal~ 1 [Pri~ 1 [No]
## # i 2,439 more rows
## # i 9 more variables: V012 <dbl+lbl>, V190 <dbl+lbl>, V312New <dbl+lbl>,
## #   Age_Gap <dbl+lbl>, V201 <dbl>, CEB <dbl+lbl>, `filter_$` <dbl+lbl>,
## #   V001 <dbl>, V005 <dbl>
```

```
names(bdhs)
```

```
## [1] "V013"          "V024"          "V025"          "V106"
## [5] "V130"          "V151"          "V701"          "WomenEmpowerment"
```

```
## [9] "V012"          "V190"          "V312New"       "Age_Gap"
## [13] "V201"          "CEB"           "filter_$"      "V001"
## [17] "V005"
```

```
bdhs <- bdhs %>%
  rename(
    cluster_id = V001,
    current_age = V012,
    sampling_weight = V005,
    wealth_index= V190,
    respondent_education = V106,
    partner_education = V701,
    division = V024,
    contraceptive_status= V312New)
names(bdhs)
```

```
## [1] "V013"          "division"       "V025"
## [4] "respondent_education" "V130"          "V151"
## [7] "partner_education" "WomenEmpowerment" "current_age"
## [10] "wealth_index"     "contraceptive_status" "Age_Gap"
## [13] "V201"            "CEB"           "filter_$"
## [16] "cluster_id"      "sampling_weight"
```

```
bdhs$CEB
```

```
## <labelled<double>[2449]>: Children ever born (groups)
## [1] 1 0 0 1 1 1 1 1 1 1 0 0 1 0 1 0 1 1 1 1 0 1 0 0 0 0 1 1 0 0 0 0 0 1 1 0 0
## [38] 1 0 1 0 1 0 0 0 1 0 1 0 0 1 1 0 0 0 0 0 1 0 0 0 1 1 0 0 0 1 0 0 0 0 0 0 1
## [75] 0 0 0 1 0 0 0 1 0 0 0 1 0 0 1 1 1 1 1 0 0 1 0 1 0 0 0 0 0 1 0 0 1 0 1 0 1
## [112] 1 0 0 1 1 0 0 1 0 1 1 0 0 1 0 0 1 1 0 1 0 0 1 1 1 1 0 0 0 0 0 0 0 1 1 0 1
## [149] 0 1 1 1 0 0 0 1 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 0 1 1 0 0 0 0 1 0 0 1 1 1
## [186] 0 0 1 0 1 0 0 1 0 1 1 0 0 0 1 0 1 0 1 1 0 0 1 0 0 0 1 0 0 0 0 0 0 0 0 0 1
## [223] 0 0 1 0 0 0 1 1 1 1 0 1 1 1 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 1 1
## [260] 0 0 0 1 1 0 0 0 1 0 0 0 0 0 0 0 0 1 1 1 0 0 0 0 0 0 0 1 1 1 0 0 0 1 0 1 1 1
## [297] 1 0 1 1 1 1 0 1 1 1 1 0 0 0 1 1 0 0 1 0 0 1 1 1 0 0 0 0 0 1 1 1 0 1 0 1 1
## [334] 1 1 1 1 1 1 1 0 0 0 1 1 0 0 1 1 1 1 1 0 1 0 0 0 1 0 0 0 0 1 1 0 0 0 1 0 1
## [371] 0 0 0 1 0 1 0 0 0 1 1 1 1 1 0 0 1 1 1 1 1 0 0 1 1 1 0 0 0 1 0 1 0 1 0 0 1
## [408] 1 1 1 0 0 1 0 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 1 0 0 0 1 0 1 0 0 1
## [445] 1 0 0 1 1 0 0 1 1 1 0 0 1 1 0 1 0 1 0 1 0 1 1 0 0 1 0 1 1 1 1 0 0 0 1 0 1 1
## [482] 1 0 0 0 0 1 1 0 0 0 0 0 0 1 0 1 1 0 1 0 1 0 1 0 0 1 0 0 0 0 1 0 0 1 0 0 1
## [519] 1 1 1 1 1 1 0 0 0 1 0 1 1 1 0 1 0 0 0 0 0 0 1 0 1 0 1 0 1 1 0 0 1 1 1 0 1
## [556] 0 1 1 1 1 1 0 0 1 0 1 0 1 0 0 1 0 1 0 1 1 1 1 0 1 1 0 1 0 1 1 0 0 0 0 0 1
## [593] 0 0 1 0 1 1 1 0 0 0 1 0 0 1 1 1 0 1 1 0 0 0 0 0 1 0 0 0 0 1 1 0 1 0 0 0 1
## [630] 1 0 1 1 1 0 1 0 1 1 0 1 1 1 1 0 0 0 1 0 0 0 0 1 0 1 1 1 0 0 0 1 0 0 1 0 0
## [667] 0 0 1 0 1 0 1 1 0 1 1 1 1 0 0 1 1 1 0 1 0 1 1 0 1 0 1 1 0 1 1 1 0 1 1 0 1
## [704] 0 0 0 0 0 0 0 0 0 1 0 1 1 0 1 0 1 1 1 0 1 1 0 0 0 0 0 1 0 0 1 1 1 0 0 0 1
## [741] 1 0 1 1 1 1 0 0 0 1 1 0 1 0 0 1 0 0 1 1 0 0 0 1 0 1 1 1 1 0 1 0 1 0 0 1 1
## [778] 1 0 0 1 1 0 0 0 1 0 0 1 0 0 0 0 1 0 1 1 1 0 1 0 1 1 1 0 0 0 1 0 0 0 0 0 1
## [815] 0 0 0 1 0 0 0 0 0 0 0 0 1 1 0 0 0 0 1 1 1 1 0 0 0 1 0 1 0 0 0 0 1 0 0 1 1
## [852] 0 1 0 1 1 0 1 0 0 1 0 1 1 1 0 0 0 0 1 1 0 1 1 1 0 1 0 0 1 0 1 1 1 1 0 0 0
## [889] 0 0 0 1 1 1 1 0 1 1 0 1 1 0 1 1 1 1 1 0 1 0 0 1 1 0 1 0 1 1 1 0 0 0 1 1 1
## [926] 1 1 0 1 0 1 0 1 1 0 0 1 0 1 0 1 1 0 0 0 1 0 0 0 0 1 1 1 1 1 1 0 0 1 0 0 0
## [963] 0 0 0 1 0 0 1 0 1 1 1 0 0 1 0 1 1 1 0 1 0 0 1 1 0 0 1 0 0 1 1 0 1 1 0 0 0
```

```

## [1000] 0 1 1 0 1 1 1 1 0 0 0 1 0 0 1 1 1 0 1 1 0 1 1 0 1 0 1 1 0 1 1 1 1 0 0 1 1
## [1037] 1 0 0 1 0 0 0 1 1 0 1 1 1 0 0 0 0 0 1 0 1 1 1 1 0 0 1 1 1 0 1 1 0 0 1 1 0
## [1074] 1 0 0 0 1 0 1 0 0 0 0 0 1 0 0 1 1 1 1 1 1 0 0 0 0 1 0 0 0 0 1 1 0 1 1 0 0
## [1111] 1 1 0 1 0 1 1 0 0 1 0 0 0 0 1 0 0 1 1 0 0 0 0 0 1 1 1 0 0 1 1 0 0 0 1 1 0
## [1148] 0 1 0 1 1 1 0 0 1 0 1 0 1 1 0 0 1 1 1 0 1 0 1 0 0 0 0 1 0 0 1 0 1 0 0 0 0
## [1185] 0 1 0 1 1 0 0 1 0 1 1 0 0 1 1 1 1 0 0 1 0 0 1 1 0 1 1 0 0 0 1 0 1 1 1 1 0
## [1222] 0 0 1 0 1 0 1 0 0 1 1 1 1 0 1 1 0 1 0 0 1 0 0 0 1 1 0 1 1 1 0 1 0 1 1 1 0
## [1259] 1 0 0 1 1 0 0 1 0 0 1 1 0 0 1 1 0 0 1 0 0 1 1 1 0 1 1 1 0 0 1 0 0 1 0 0 1
## [1296] 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 0 0 1 1 1 1 0 0 1 0 0 1 1 1 0 1 0 0 1 1 0 0
## [1333] 0 0 1 0 0 0 0 1 0 0 0 0 0 1 0 0 1 0 1 0 1 0 1 0 1 0 0 0 1 1 0 0 0 0 0 0 0
## [1370] 0 1 0 1 0 1 1 1 1 1 0 1 0 0 0 1 0 0 0 0 0 0 1 1 1 1 0 1 0 1 0 0 0 1 0 1 1
## [1407] 0 1 1 0 1 0 0 0 0 0 1 0 0 1 1 0 1 0 1 0 0 1 0 0 1 0 0 0 1 0 1 1 0 0 0 0 0
## [1444] 1 1 0 1 1 1 0 1 0 0 0 0 0 0 0 1 0 0 1 1 1 0 0 0 1 1 1 0 0 1 0 0 0 0 0 0 1
## [1481] 1 0 0 0 1 0 0 0 1 1 1 0 1 0 0 1 0 0 1 1 1 1 0 0 0 0 0 0 0 1 0 0 1 1 0 1 1
## [1518] 1 1 1 0 0 0 1 0 1 0 0 0 0 0 0 1 1 1 0 1 0 0 0 1 0 0 0 1 1 0 0 0 1 0 0 1 0
## [1555] 1 0 0 0 0 0 0 0 1 1 0 1 0 0 0 0 1 1 0 1 0 1 1 0 0 0 1 0 0 1 1 1 1 0 1 0 0
## [1592] 0 1 1 0 1 0 1 1 1 0 1 0 0 0 1 0 1 0 0 1 0 0 0 0 0 0 0 0 0 1 1 0 1 0 0 1 0 1
## [1629] 0 1 1 1 0 1 0 0 1 1 0 1 1 1 0 0 0 1 0 1 0 0 1 0 1 1 0 1 1 1 0 1 0 0 0 0 0
## [1666] 0 0 1 1 1 0 1 0 1 1 1 0 1 0 1 0 0 0 1 1 0 0 0 0 0 1 0 1 1 0 0 0 1 0 0 1 0
## [1703] 1 0 1 0 0 0 0 1 1 0 0 0 0 0 1 0 0 1 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 1 1 0 0
## [1740] 0 0 0 0 0 0 0 0 0 1 0 1 0 1 0 0 1 1 1 1 0 0 0 1 0 0 0 1 0 1 1 1 0 0 0 1 0
## [1777] 1 0 0 1 1 0 0 0 1 0 1 1 0 0 1 1 0 1 0 0 1 0 0 1 1 0 0 1 0 0 1 1 1 1 0 1 0
## [1814] 1 0 0 1 1 1 1 1 0 0 0 0 0 1 1 1 1 0 1 0 0 1 1 0 0 1 0 1 0 0 0 1 1 1 0 0 0
## [1851] 1 0 1 1 1 1 1 1 0 0 1 0 0 1 0 1 0 0 0 0 0 0 0 1 1 0 0 1 1 0 0 0 0 1 0 0 0
## [1888] 1 1 1 0 0 0 0 0 0 1 1 1 1 1 0 1 0 0 1 1 1 1 0 0 0 0 1 1 0 1 0 0 0 0 1 1 0
## [1925] 1 1 0 1 1 0 0 1 1 1 1 1 0 1 1 0 0 1 0 0 1 0 1 1 0 0 1 1 1 0 0 1 1 1 0 0 0
## [1962] 0 1 0 1 0 1 1 0 0 0 1 0 0 1 1 0 0 0 0 1 1 1 1 0 0 0 1 0 0 0 1 1 0 1 1 1 1
## [1999] 0 0 1 0 1 1 1 1 1 0 1 0 0 0 1 0 0 1 0 1 0 1 0 0 0 1 1 1 1 0 0 0 0 0 1 1 1
## [2036] 1 0 1 1 1 0 0 0 1 1 0 1 1 1 1 0 0 0 1 0 0 1 0 0 1 0 1 0 0 0 0 0 1 0 0 0 1
## [2073] 0 1 1 1 0 1 0 1 1 0 0 1 1 0 1 0 0 0 1 1 1 1 1 0 0 1 0 1 1 1 0 1 0 1 0 0 0
## [2110] 0 0 1 0 1 0 1 1 1 1 0 1 1 0 1 0 1 0 0 0 1 0 0 1 1 0 0 1 0 1 0 0 1 0 1 1 0
## [2147] 0 1 1 0 0 0 0 1 1 1 0 1 1 0 0 0 1 0 0 1 0 0 0 1 0 1 1 1 0 1 0 0 0 0 0 1 1
## [2184] 1 1 0 1 0 1 1 0 0 0 1 1 1 1 0 1 0 1 0 1 1 1 1 0 0 0 0 1 1 0 0 1 1 1 1 1 0
## [2221] 0 1 1 0 0 1 0 0 1 0 1 1 1 0 1 1 1 1 1 0 0 1 1 1 0 1 0 0 1 1 0 1 1 1 1 1 1
## [2258] 1 1 1 0 0 1 0 0 1 1 0 0 0 1 0 0 1 0 0 1 1 0 0 0 0 1 1 0 1 0 1 1 1 1 1 0 1
## [2295] 0 0 1 0 0 1 0 1 0 0 0 0 0 1 0 0 1 0 0 1 0 1 1 0 0 1 0 1 1 1 1 0 1 0 0 0 1
## [2332] 0 0 0 0 1 0 0 1 0 1 0 0 0 1 1 0 0 0 0 0 0 1 1 0 0 1 0 0 0 0 0 0 1 0 1 1 1
## [2369] 0 1 0 1 0 1 0 1 1 0 1 0 0 0 0 0 0 1 1 1 0 0 0 1 1 0 0 0 1 1 1 1 0 0 0 0 1
## [2406] 1 1 0 1 0 1 1 0 0 0 1 1 1 0 1 0 0 0 0 1 1 0 0 0 0 1 0 0 0 1 1 0 1 1 0 0 0
## [2443] 0 0 0 0 1 1 1
##
## Labels:
##   value      label
##      0 No Children
##      1 One or more

```

```

bdhs <- bdhs %>%
  mutate(
    weight = sampling_weight / 1000000,
    cluster_id = as.factor(cluster_id),
    CEB_binary = ifelse(CEB > 0, 1, 0), # use numeric binary
    education = as_factor(respondent_education),
    partner_education = as_factor(partner_education),
    division = as_factor(division),

```

```

age_gap = as_factor(Age_Gap),
wealth = as_factor(wealth_index),
age = as.factor(current_age),
age_group_5yr = as_factor(V013),
WomenEmpowerment = as_factor(WomenEmpowerment),
contraceptive_status = as_factor(contraceptive_status)
)

```

1 2. Descriptive Analysis

```
table(bdhs$education)
```

```
##
## No education      Primary      Secondary      Higher
##           40           339           1879           191
```

```
table(bdhs$CEB_binary)
```

```
##
##      0      1
## 1340 1109
```

#Multilevel Logistic regression model

```

model <- glmer(CEB_binary ~ education + partner_education + division +
               age_gap + wealth + age + WomenEmpowerment + contraceptive_status +
               (1 | cluster_id),
               data = bdhs,
               family = binomial(link = "logit"),
               weights = weight,
               control = glmerControl(optimizer = "bobyqa"))

```

```
## Warning in eval(family$initialize, rho): non-integer #successes in a binomial
## glm!
```

```
## boundary (singular) fit: see help('isSingular')
```

```
summary(model)
```

```
## Warning in vcov.merMod(object, use.hessian = use.hessian): variance-covariance matrix computed from :
## not positive definite or contains NA values: falling back to var-cov estimated from RX
```

```
## Warning in vcov.merMod(object, correlation = correlation, sigm = sig): variance-covariance matrix computed from :
## not positive definite or contains NA values: falling back to var-cov estimated from RX
```

```

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula: CEB_binary ~ education + partner_education + division + age_gap +
## wealth + age + WomenEmpowerment + contraceptive_status +
## (1 | cluster_id)
## Data: bdhs
## Weights: weight
## Control: glmerControl(optimizer = "bobyqa")
##
##          AIC          BIC      logLik -2*log(L)  df.resid
##      1182.5      1327.6      -566.2    1132.5      2424
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.1313 -0.5123 -0.1922  0.5232  4.4070
##
## Random effects:
## Groups      Name                Variance Std.Dev.
## cluster_id (Intercept) 0                0
## Number of obs: 2449, groups: cluster_id, 54
##
## Fixed effects:
##
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)      0.63095    0.84592   0.746 0.455740
## educationPrimary    -0.04806    0.58911  -0.082 0.934984
## educationSecondary  -0.51375    0.57268  -0.897 0.369663
## educationHigher    -1.53151    0.62691  -2.443 0.014567 *
## partner_educationPrimary -0.22102    0.34073  -0.649 0.516551
## partner_educationSecondary -0.88989    0.32252  -2.759 0.005795 **
## partner_educationHigher -1.07727    0.36086  -2.985 0.002833 **
## divisionChattogram    0.48937    0.46706   1.048 0.294746
## divisionDhaka        0.64560    0.42607   1.515 0.129709
## divisionKhulna       0.53188    0.41061   1.295 0.195201
## divisionMymensingh    0.03942    0.41160   0.096 0.923695
## divisionRajshahi      0.26405    0.40402   0.654 0.513386
## divisionRangpur       0.56312    0.40272   1.398 0.162028
## divisionSylhet       -0.11630    0.43295  -0.269 0.788224
## age_gap6-10          -0.85680    0.20282  -4.225 2.39e-05 ***
## age_gap<=5           -0.92041    0.22617  -4.070 4.71e-05 ***
## wealthMiddle         -0.23889    0.14125  -1.691 0.090781 .
## wealthRich           -0.77462    0.22197  -3.490 0.000484 ***
## age16                1.06643    0.36913   2.889 0.003864 **
## age17                1.61042    0.35417   4.547 5.44e-06 ***
## age18                2.10797    0.34014   6.197 5.74e-10 ***
## age19                2.76989    0.34336   8.067 7.21e-16 ***
## WomenEmpowermentNo   -0.57647    0.29489  -1.955 0.050600 .
## contraceptive_statusNo -1.34015    0.15708  -8.532 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 24 > 12.
## Use print(x, correlation=TRUE) or

```

```
##      vcov(x)          if you need it

## optimizer (bobyqa) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')
```

2 Odds Ratios and Confidence Intervals

```
exp(coef(summary(model))[, "Estimate"])
```

```
## Warning in vcov.merMod(object, use.hessian = use.hessian): variance-covariance matrix computed from :
## not positive definite or contains NA values: falling back to var-cov estimated from RX

## Warning in vcov.merMod(object, correlation = correlation, sigma = sig): variance-covariance matrix co
## not positive definite or contains NA values: falling back to var-cov estimated from RX
```

```
##              (Intercept)          educationPrimary
##              1.8794038             0.9530793
##      educationSecondary          educationHigher
##              0.5982479             0.2162088
##      partner_educationPrimary partner_educationSecondary
##              0.8017001             0.4107000
##      partner_educationHigher      divisionChattogram
##              0.3405226             1.6312926
##              divisionDhaka          divisionKhulna
##              1.9071258             1.7021314
##              divisionMymensingh      divisionRajshahi
##              1.0402108             1.3021991
##              divisionRangpur          divisionSylhet
##              1.7561488             0.8902098
##              age_gap6-10             age_gap<=5
##              0.4245183             0.3983555
##              wealthMiddle            wealthRich
##              0.7875005             0.4608804
##              age16                   age17
##              2.9049866             5.0048928
##              age18                   age19
##              8.2315001             15.9568856
##      WomenEmpowermentNo      contraceptive_statusNo
##              0.5618808             0.2618053
```

```
exp(confint(model, method = "Wald"))
```

```
## Warning in vcov.merMod(object): variance-covariance matrix computed from finite-difference Hessian i
## not positive definite or contains NA values: falling back to var-cov estimated from RX
```

```
##              2.5 %      97.5 %
## .sig01          NA          NA
## (Intercept)    0.35807376  9.8643327
## educationPrimary 0.30038271  3.0240094
```

## educationSecondary	0.19472377	1.8379913
## educationHigher	0.06327752	0.7387497
## partner_educationPrimary	0.41113396	1.5632937
## partner_educationSecondary	0.21826944	0.7727812
## partner_educationHigher	0.16787336	0.6907327
## divisionChattogram	0.65308228	4.0747017
## divisionDhaka	0.82739192	4.3958959
## divisionKhulna	0.76116993	3.8063134
## divisionMymensingh	0.46426613	2.3306429
## divisionRajshahi	0.58990006	2.8745928
## divisionRangpur	0.79755698	3.8668817
## divisionSylhet	0.38103451	2.0797946
## age_gap6-10	0.28527226	0.6317325
## age_gap<=5	0.25571331	0.6205666
## wealthMiddle	0.59706331	1.0386788
## wealthRich	0.29829434	0.7120845
## age16	1.40910474	5.9888713
## age17	2.49993392	10.0198456
## age18	4.22617474	16.0328427
## age19	8.14097957	31.2766044
## WomenEmpowermentNo	0.31523448	1.0015084
## contraceptive_statusNo	0.19243025	0.3561914

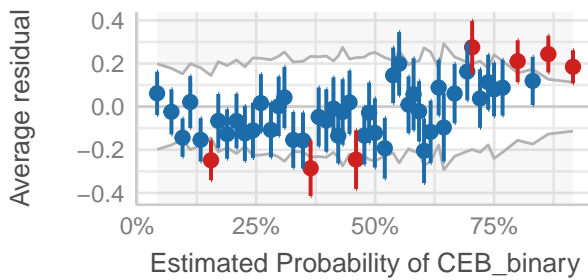
3 Model Diagnostics

```
check_model(model)
```

```
## Cannot simulate residuals for models of class `glmerMod`. Please try
## `check_model(..., residual_type = "normal")` instead.
```

Binned Residuals

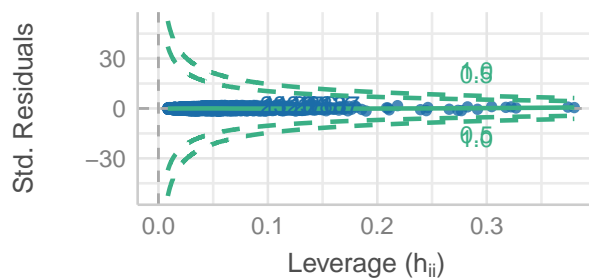
Points should be within error bounds



Within error bounds — no — yes

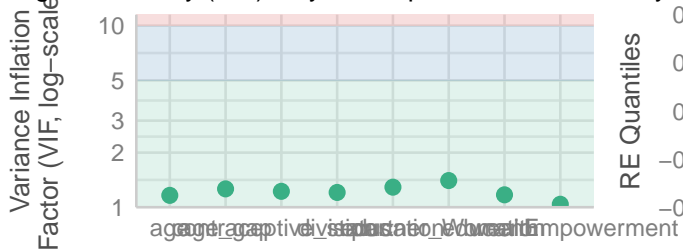
Influential Observations

Points should be inside the contour lines



Collinearity

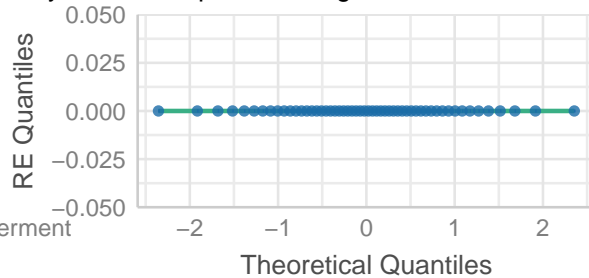
High collinearity (VIF) may inflate parameter uncertainty



Low (< 5)

Normality of Random Effects (cluster_id)

Points should be plotted along the line



```
model_performance(model)
```

```
## boundary (singular) fit: see help('isSingular')
```

```
## Random effect variances not available. Returned R2 does not account for random effects.
```

```
## boundary (singular) fit: see help('isSingular')
```

```
## # Indices of model performance
```

```
##
```

```
## AIC      |      AICc |      BIC | R2 (cond.) | R2 (marg.) | RMSE | Sigma
```

```
## -----|-----|-----|-----|-----|-----|-----
```

```
## 1182.468 | 1183.004 | 1327.553 |          |          | 0.292 | 0.446 | 1.000
```

```
##
```

```
## AIC      | Log_loss | Score_log | Score_spherical
```

```
## -----|-----|-----|-----
```

```
## 1182.468 |    0.583 |      -Inf |      4.100e-04
```

4 Fit standard logistic regression model (no random effects)


```
model_simple <- glm(CEB_binary ~ education + partner_education + division +
  age_gap + wealth + age + WomenEmpowerment + contraceptive_status,
  data = bdhs,
  family = binomial(link = "logit"),
  weights = weight)
```

```
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
```

```
summary(model_simple)
```

```
##
## Call:
## glm(formula = CEB_binary ~ education + partner_education + division +
##      age_gap + wealth + age + WomenEmpowerment + contraceptive_status,
##      family = binomial(link = "logit"), data = bdhs, weights = weight)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)      0.77193    0.84404   0.915  0.36042
## educationPrimary -0.25947    0.59572  -0.436  0.66316
## educationSecondary -0.78439    0.57984  -1.353  0.17613
## educationHigher   -1.74634    0.63335  -2.757  0.00583 **
## partner_educationPrimary -0.07776    0.33585  -0.232  0.81690
## partner_educationSecondary -0.73724    0.31715  -2.325  0.02009 *
## partner_educationHigher  -0.91856    0.35577  -2.582  0.00983 **
## divisionChattogram    0.60734    0.46634   1.302  0.19280
## divisionDhaka         0.61577    0.42578   1.446  0.14812
## divisionKhulna        0.62623    0.41063   1.525  0.12724
## divisionMymensingh     0.14652    0.41169   0.356  0.72192
## divisionRajshahi       0.37323    0.40415   0.924  0.35575
## divisionRangpur        0.68515    0.40303   1.700  0.08913 .
## divisionSylhet        -0.01292    0.43317  -0.030  0.97620
## age_gap6-10           -0.86901    0.20132  -4.317 1.58e-05 ***
## age_gap<=5            -0.97615    0.22519  -4.335 1.46e-05 ***
## wealthMiddle          -0.24358    0.14070  -1.731  0.08342 .
## wealthRich            -0.63624    0.21914  -2.903  0.00369 **
## age16                  0.91547    0.35682   2.566  0.01030 *
## age17                  1.39496    0.34141   4.086 4.39e-05 ***
## age18                  1.98862    0.32669   6.087 1.15e-09 ***
## age19                  2.55471    0.32934   7.757 8.68e-15 ***
## WomenEmpowermentNo    -0.54284    0.29358  -1.849  0.06446 .
## contraceptive_statusNo -1.32795    0.15625  -8.499 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 1741.9  on 2448  degrees of freedom
## Residual deviance: 1468.5  on 2425  degrees of freedom
## AIC: 1604.3
##
## Number of Fisher Scoring iterations: 4
```

```
# Likelihood Ratio Test to compare models
anova(model_simple, model, test = "Chisq")
```

```
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
## Warning in eval(family$initialize): non-integer #successes in a binomial glm!
```

```
## Analysis of Deviance Table
##
## Model: binomial, link: logit
##
## Response: CEB_binary
##
## Terms added sequentially (first to last)
##
##
```

	Df	Deviance	Resid. Df	Resid. Dev	Pr(>Chi)
## NULL			2448	1741.9	
## education	3	17.140	2445	1724.8	0.0006614 ***
## partner_education	3	16.454	2442	1708.3	0.0009150 ***
## division	7	12.011	2435	1696.3	0.1002043
## age_gap	2	10.941	2433	1685.3	0.0042097 **
## wealth	2	7.318	2431	1678.0	0.0257531 *
## age	4	128.926	2427	1549.1	< 2.2e-16 ***
## WomenEmpowerment	1	0.980	2426	1548.1	0.3221401
## contraceptive_status	1	79.576	2425	1468.5	< 2.2e-16 ***

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Compare model fit using AIC
AIC(model, model_simple)
```

```
##           df      AIC
## model      25 1182.468
## model_simple 24 1604.323
```

5 10. Publication-Ready Table

```
tab_model(model, show.ci = TRUE, show.icc = TRUE, show.re.var = TRUE)
```

```
## boundary (singular) fit: see help('isSingular')
```

CEB_binary

Predictors	Odds Ratios	CI	p
(Intercept)	1.88	0.00 – Inf	0.456
Highest educationlevel: Primary	0.95	0.00 – Inf	0.935
Highest educationlevel: Secondary	0.60	0.00 – Inf	0.370
Highest educationlevel: Higher	0.22	0.00 – Inf	0.015
Husband/partner'seducation level: Primary	0.80	0.00 – Inf	0.517
Husband/partner'seducation level:Secondary	0.41	0.00 – Inf	0.006
Husband/partner'seducation level: Higher	0.34	0.00 – Inf	0.003
Division: Chattogram	1.63	0.00 – Inf	0.295

Division: Dhaka

1.91

0.00 – Inf

0.130

Division: Khulna

1.70

0.00 – Inf

0.195

Division: Mymensingh

1.04

0.00 – Inf

0.924

Division: Rajshahi

1.30

0.00 – Inf

0.513

Division: Rangpur

1.76

0.00 – Inf

0.162

Division: Sylhet

0.89

0.00 – Inf

0.788

age_gap6-10

0.42

0.00 – Inf

<0.001

age: Age Gap betweenHasband and Respondant:<=5

0.40

0.00 – Inf

<0.001

Wealth index combined:Middle

0.79

0.00 – Inf

0.091

Wealth index combined:Rich
0.46
0.00 – Inf
<0.001
age: age16
2.90
0.00 – Inf
0.004
age: age17
5.00
0.00 – Inf
<0.001
age: age18
8.23
0.00 – Inf
<0.001
age: age19
15.96
0.00 – Inf
<0.001
Respondant can makedecisions: No
0.56
0.00 – Inf
0.051
Contraceptive Use: No
0.26
0.00 – Inf
<0.001
Random Effects
2
3.29
00 cluster__id
0.00
N cluster__id
54
Observations

2449

Marginal R2 / Conditional R2

0.292 / NA