Marriage Timing Discrete Time Event History Analysis Code for the ChitwanABM

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Follows analysis of Yabiku (2006):

> Yabiku, S. T. 2006. Land use and marriage timing in Nepal. Population & Environment 27 (5):445-461.

Uses the `glmer` function from the R `glmer` package to conduct a multilevel discrete-time event history analysis of marriage timing using the monthly Chitwan Valley Family Study (CVFS) household registry data.

```
library(ggplot2)
```

```
## Need help? Try the ggplot2 mailing list:
## http://groups.google.com/group/ggplot2.
```

```
library(lme4)
```

```
## Loading required package: Matrix
```

```
## Loading required package: lattice
```

```
## Attaching package: 'lme4'
```

```
## The following object(s) are masked from 'package:stats':
##
## AIC, BIC
```

```
library(arm)  # for se.coef, se.fixef
```

```
## Loading required package: MASS
```

```
## Loading required package: R2WinBUGS
```

```
## Loading required package: coda
```

```
## Attaching package: 'coda'
```

```
## The following object(s) are masked from 'package:lme4':
##
## HPDinterval
```

```
## Loading required package: abind
```

```
## Loading required package: foreign
```

```
## arm (Version 1.5-08, built: 2012-10-3)
```

```
## Working directory is
## C:/Users/azvoleff/Code/R/Chitwan_R_files/Event_History_Analysis
```

```
## Attaching package: 'arm'
```

```
## The following object(s) are masked from 'package:coda':
##
## traceplot
```

```
theme_set(theme_grey(base_size = 10))

load("data/marriage_data-longformat-up_to_month_90.Rdata")

# Drop 'other' ethnicity for consistency with Yabiku et al. (2006)
marit_long <- marit_long[!(marit_long$ethnic == "Other"), ]
marit_long$ethnic <- factor(marit_long$ethnic)

# To stabilize numerical algorithm (to avoid 'false convergence' error in
# glmer), try categorizing age by decade, converting time to decades and
# try adding a continuous age variable in decades. This makes the betas on
# age and time larger and helps stabilizes the optimization algorithm.
marit_long$timeyears <- marit_long$time/12
marit_long$agedecades <- marit_long$age/10

# Create a monthly factor that can be used to remove the effects of
# seasonal variation in marriage rates
marit_long$month <- factor(marit_long$time%%12 + 1)

# Load LHC to get in_school variables and labor variables
lhc <- read.xport("G:/Data/Nepal/CVFS_Public/20120722_Chitwan_Unrestricted_Data/ICPSR_04538/DS0013/04538_0013_data.xpt")
old_respID <- sprintf("%07i", lhc$RESPID)
NBHID <- sprintf("%03i", as.numeric(substr(old_respID, 1, 3)))
HHID <- sprintf("%03i", as.numeric(substr(old_respID, 4, 5)))
SUBJID <- sprintf("%03i", as.numeric(substr(old_respID, 6, 7)))
lhc$respid <- paste(NBHID, HHID, SUBJID, sep = "")
lhc_vars <- with(lhc, data.frame(respid, wage_job_ever = WAGEYN, salaried_job_ever = SALYN))
lhc_vars$in_school_1996 <- lhc$SCHL2053
# Code 1, and 2 (beginning and continuation, as attending. Code 3 and 4
# (ending, and beg+end in same year) as not attending. Code missing (-1
# and -2) as NA.
lhc_vars$in_school_1996[lhc_vars$in_school_1996 == 2] <- 1
lhc_vars$in_school_1996[lhc_vars$in_school_1996 == 3] <- 0
lhc_vars$in_school_1996[lhc_vars$in_school_1996 == 4] <- 0
lhc_vars$in_school_1996[lhc_vars$in_school_1996 == -1] <- NA
lhc_vars$in_school_1996[lhc_vars$in_school_1996 == -2] <- NA
marit_long <- merge(marit_long, lhc_vars, all.x = TRUE)

# Merge community context variables
load("T:/Nepal/ICPSR_0538_Restricted/Recode/recoded_NBH_data.Rdata")
nbh_level_vars_cols <- grep("^(NEIGHID|elec_avail|avg_yrs_services_lt15|dist_nara|HLTHFT_1996|SCHLFT_1996|BUSFT_1996|MARFT_1996|EMPFT_1996)$",
    names(nbh_recode))
nbh_level_vars <- nbh_recode[nbh_level_vars_cols]
nbh_level_vars$NEIGHID <- as.numeric(nbh_level_vars$NEIGHID)
marit_long <- merge(marit_long, nbh_level_vars, by.x = "originalNBH", by.y = "NEIGHID",
    all.x = TRUE)
```

Basic Statistics

Total number of person-month records: 46000. Now look at a table of how those records are distributed (0 being unmarried, 1 being married).

```
table(marit_long$marit, exclude = NULL)
```

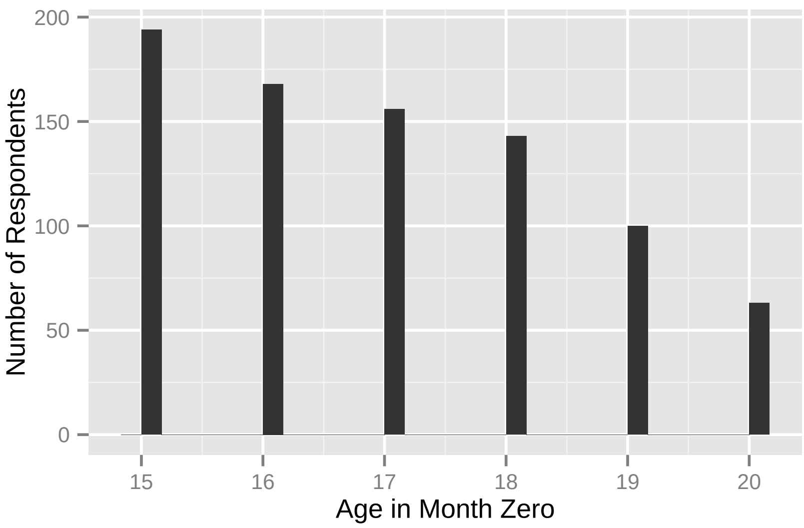
```
##
##     0     1  <NA>
## 45513   487     0
```

Make a quick plot of the age distribution of the sample in the first month of data collection (when all are unmarried)

```
qplot(age, geom = "bar", data = marit_long[marit_long$time == 1, ], xlab = "Age in Month Zero",
    ylab = "Number of Respondents")
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust
## this.
```

```
## Warning: position_stack requires constant width: output may be incorrect
```



Age distribution of sample in initial month of data collection

Also plot the age at marriage

Note

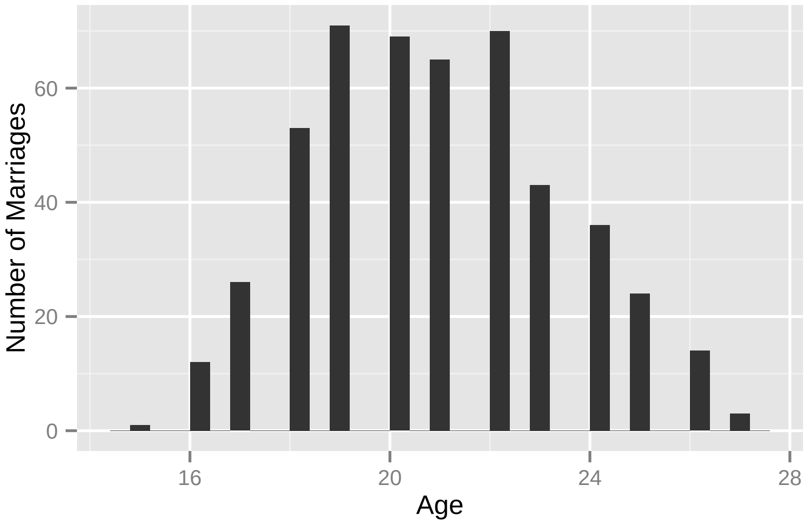
This sample only includes 90 months of data from people who were 15-20 in 1996, so the max possible age at marriage in this sample is 27.5. When tested with a sample including those from age 15-90, the number of marriages by age is:

```
>table(marit_long[marit_long$marit==1,]$age)
15  16  17  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  34  35  41
1   12 26 53 71 69 66 79 56 54 38 29 17  8 12  4  4  1  1  1  1
```

Given that there are so few marriages of those above age 30, the assumption is made in the ChitwanABM that if you are not married by age 30, you will not be getting married. Hence there is a "maximum_marriage_age" parameter in the model

```
qplot(age, geom = "bar", data = marit_long[marit_long$marit == 1, ], xlab = "Age",
    ylab = "Number of Marriages")
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust
## this.
```



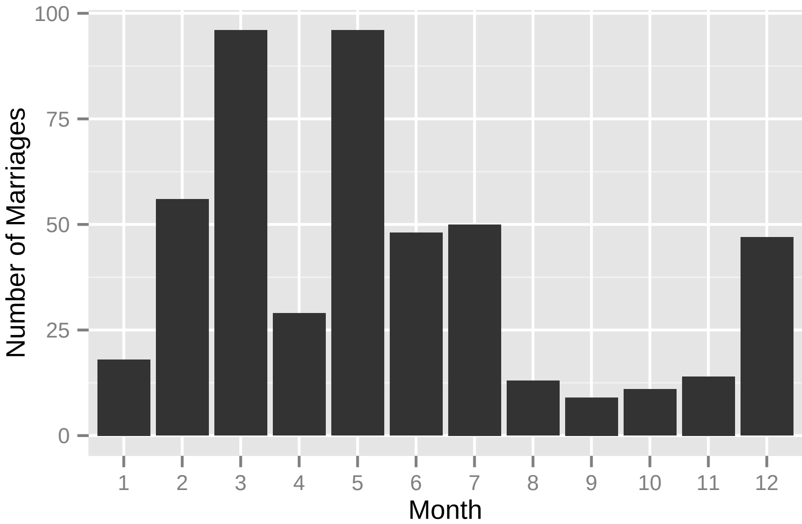
Age at first marriage

```
table(marit_long[marit_long$marit == 1, ]$age)
```

```
##
## 15 16 17 18 19 20 21 22 23 24 25 26 27
##  1 12 26 53 71 69 65 70 43 36 24 14  3
```

Note that marriage is seasonal, so include a dummy variables for each month later on in the models:

```
qplot(month, geom = "bar", data = marit_long[marit_long$marit == 1, ], xlab = "Month",
    ylab = "Number of Marriages")
```



plot of chunk marriages-month-hist

Check cross tabs of marit with the categorical predictors:

```
xtabs(~marit_long$age + marit_long$marit, exclude = NULL)
```

```
##                marit_long$marit
## marit_long$age    0    1
##             15  580    1
##             16 2721   12
##             17 4421   26
##             18 5727   53
##             19 6422   71
##             20 6486   69
##             21 6051   65
##             22 5107   70
##             23 3652   43
##             24 2252   36
##             25 1261   24
##             26  615   14
##             27  194    3
##             28   24    0
```

```
xtabs(~marit_long$marit + marit_long$ethnic, exclude = NULL)
```

```
##                 marit_long$ethnic
## marit_long$marit UpHindu HillTibeto LowHindu Newar TeraiTibeto
##                0   25182       5385     3498  4280        7168
##                1     264         63       37    35          88
```

```
xtabs(~marit_long$marit + marit_long$gender, exclude = NULL)
```

```
##                 marit_long$gender
## marit_long$marit  male female
```

```
##                 0 26394  19119
##                 1   200    287
```

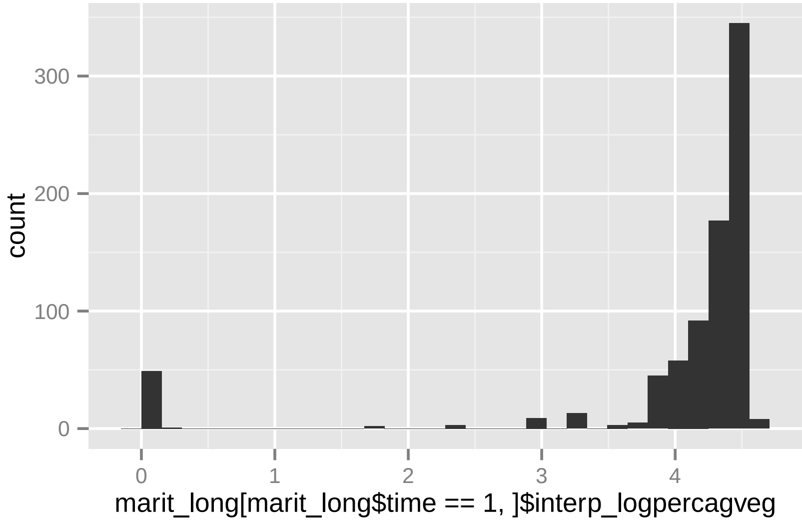
```
with(marit_long, xtabs(~age + ethnic + gender, exclude = NULL))
```

```
## , , gender = male
##
##      ethnic
## age  UpHindu HillTibeto LowHindu Newar TeraiTibeto
##   15     153         12       27    21          39
##   16     730        105      138    99         186
##   17    1204        303      267   144         359
##   18    1643        398      381   183         490
##   19    2002        445      374   206         542
##   20    2213        528      352   236         537
##   21    2127        513      303   264         533
##   22    1866        428      236   264         455
##   23    1299        378      186   215         330
##   24     844        240       93   141         205
##   25     464        145       33    82          87
##   26     236         69       24    43          42
##   27      66         18        6     9          18
##   28       9          3        0     0           3
##
## , , gender = female
##
##      ethnic
## age  UpHindu HillTibeto LowHindu Newar TeraiTibeto
##   15     168         45       23    27          66
##   16     762        203       99   129         282
##   17    1211        280      151   191         337
##   18    1583        277      159   231         435
##   19    1677        255      183   330         479
##   20    1494        252      132   354         457
##   21    1311        183      119   336         427
##   22    1012        140      104   308         364
##   23     638        107       66   220         256
##   24     380         69       42   126         148
##   25     226         34       31    94          89
##   26     101         15        6    39          54
##   27      24          3        0    23          30
##   28       3          0        0     0           6
```

Now make a quick plot of a histogram of log(percent agricultural vegetation + 1), for the first month:

```
qplot(marit_long[marit_long$time == 1, ]$interp_logpercagveg, geom = "histogram")
```

```
## stat_bin: binwidth defaulted to range/30. Use 'binwidth = x' to adjust
## this.
```



log(percent ag. veg. + 1) for month 1

Discrete-time Event History Models

Fixed effect model

Do two fixed effects models. First do a GLM with age in years, then a GLM with age in decades. Yabiku (2006) presents results with age in years, but the `glmer` optimization routine wouldn't converge unless age was rescaled to decades. So do a GLM with age in years for comparison with the Yabiku (2006) results, but use age in decades for the final model to be included in the ABM.

```
marr_fixed <- glm(marit ~ ethnic + gender + age + I(age^2) + interp_logpercagveg +
    SCHLFT_1996 + HLTHFT_1996 + BUSFT_1996 + MARFT_1996 + EMPFT_1996 + schooling_yrs +
    in_school_1996 + month, data = marit_long, family = binomial)
save(marr_fixed, file = "models/marr_fixed.Rdata")
summary(marr_fixed)
```

```
##
## Call:
## glm(formula = marit ~ ethnic + gender + age + I(age^2) + interp_logpercagveg +
##     SCHLFT_1996 + HLTHFT_1996 + BUSFT_1996 + MARFT_1996 + EMPFT_1996 +
##     schooling_yrs + in_school_1996 + month, family = binomial,
##     data = marit_long)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -0.457  -0.168  -0.118  -0.079   3.690
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -1.52e+01   2.74e+00   -5.53  3.1e-08 ***
## ethnicHillTibeto     1.71e-01   1.51e-01    1.14  0.25583
## ethnicLowHindu       1.41e-02   1.92e-01    0.07  0.94153
## ethnicNewar         -2.41e-01   2.00e-01   -1.20  0.22890
## ethnicTeraiTibeto   -9.87e-02   1.49e-01   -0.66  0.50823
## genderfemale         8.09e-01   1.02e-01    7.93  2.3e-15 ***
## age                  7.45e-01   2.59e-01    2.88  0.00396 **
```

```
## I(age^2)            -1.45e-02   6.15e-03   -2.36  0.01810 *
## interp_logpercagveg  1.29e-01   6.99e-02    1.85  0.06420 .
## SCHLFT_1996          1.20e-02   8.11e-03    1.48  0.13771
## HLTHFT_1996         -1.14e-03   3.08e-03   -0.37  0.71069
## BUSFT_1996           4.50e-03   4.18e-03    1.08  0.28163
## MARFT_1996          -6.63e-04   3.31e-03   -0.20  0.84155
## EMPFT_1996           2.80e-03   2.73e-03    1.03  0.30474
## schooling_yrs       -2.71e-03   2.02e-02   -0.13  0.89340
## in_school_1996      -4.02e-01   1.14e-01   -3.52  0.00043 ***
## month2               1.07e+00   2.79e-01    3.82  0.00013 ***
## month3               1.58e+00   2.66e-01    5.92  3.1e-09 ***
## month4               3.58e-01   3.13e-01    1.14  0.25341
## month5               1.53e+00   2.65e-01    5.75  8.8e-09 ***
## month6               8.16e-01   2.86e-01    2.85  0.00437 **
## month7               8.78e-01   2.85e-01    3.08  0.00204 **
## month8              -3.88e-01   3.78e-01   -1.03  0.30492
## month9              -9.25e-01   4.50e-01   -2.06  0.03976 *
## month10             -6.70e-01   4.13e-01   -1.62  0.10504
## month11             -3.76e-01   3.78e-01   -0.99  0.32016
## month12              9.20e-01   2.88e-01    3.20  0.00139 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5036.9  on 42645  degrees of freedom
## Residual deviance: 4666.9  on 42619  degrees of freedom
##   (3354 observations deleted due to missingness)
## AIC: 4721
##
## Number of Fisher Scoring iterations: 8
```

```
(marr_fixed_or <- data.frame(coef = coef(marr_fixed), OR = round(exp(coef(marr_fixed)),
    4)))
```

```
##                            coef     OR
## (Intercept)         -1.516e+01 0.0000
## ethnicHillTibeto     1.713e-01 1.1868
## ethnicLowHindu       1.410e-02 1.0142
## ethnicNewar         -2.411e-01 0.7857
## ethnicTeraiTibeto   -9.868e-02 0.9060
## genderfemale         8.088e-01 2.2452
## age                  7.452e-01 2.1069
## I(age^2)            -1.453e-02 0.9856
## interp_logpercagveg  1.293e-01 1.1381
## SCHLFT_1996          1.204e-02 1.0121
## HLTHFT_1996         -1.142e-03 0.9989
## BUSFT_1996           4.502e-03 1.0045
## MARFT_1996          -6.626e-04 0.9993
## EMPFT_1996           2.801e-03 1.0028
## schooling_yrs       -2.706e-03 0.9973
## in_school_1996      -4.025e-01 0.6687
## month2               1.066e+00 2.9038
## month3               1.578e+00 4.8469
```

```
## month4                 3.579e-01 1.4303
## month5                 1.527e+00 4.6028
## month6                 8.158e-01 2.2610
## month7                 8.776e-01 2.4051
## month8                -3.879e-01 0.6785
## month9                -9.250e-01 0.3965
## month10               -6.697e-01 0.5118
## month11               -3.759e-01 0.6867
## month12                9.202e-01 2.5098
```

```
write.csv(marr_fixed_or, file = "models/marr_fixed_odds.csv")
```

```
marr_fixed_agedecades <- glm(marit ~ ethnic + gender + agedecades + I(agedecades^2) +
    interp_logpercagveg + SCHLFT_1996 + HLTHFT_1996 + BUSFT_1996 + MARFT_1996 +
    EMPFT_1996 + schooling_yrs + in_school_1996 + month, data = marit_long,
    family = binomial)
save(marr_fixed_agedecades, file = "models/marr_fixed_agedecades.Rdata")
summary(marr_fixed_agedecades)
```

```
##
## Call:
## glm(formula = marit ~ ethnic + gender + agedecades + I(agedecades^2) +
##     interp_logpercagveg + SCHLFT_1996 + HLTHFT_1996 + BUSFT_1996 +
##     MARFT_1996 + EMPFT_1996 + schooling_yrs + in_school_1996 +
##     month, family = binomial, data = marit_long)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -0.457  -0.168  -0.118  -0.079   3.690
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -1.52e+01   2.74e+00   -5.53  3.1e-08 ***
## ethnicHillTibeto     1.71e-01   1.51e-01    1.14  0.25583
## ethnicLowHindu       1.41e-02   1.92e-01    0.07  0.94153
## ethnicNewar         -2.41e-01   2.00e-01   -1.20  0.22890
## ethnicTeraiTibeto   -9.87e-02   1.49e-01   -0.66  0.50823
## genderfemale         8.09e-01   1.02e-01    7.93  2.3e-15 ***
## agedecades           7.45e+00   2.59e+00    2.88  0.00396 **
## I(agedecades^2)     -1.45e+00   6.15e-01   -2.36  0.01810 *
## interp_logpercagveg  1.29e-01   6.99e-02    1.85  0.06420 .
## SCHLFT_1996          1.20e-02   8.11e-03    1.48  0.13771
## HLTHFT_1996         -1.14e-03   3.08e-03   -0.37  0.71069
## BUSFT_1996           4.50e-03   4.18e-03    1.08  0.28163
## MARFT_1996          -6.63e-04   3.31e-03   -0.20  0.84155
## EMPFT_1996           2.80e-03   2.73e-03    1.03  0.30474
## schooling_yrs       -2.71e-03   2.02e-02   -0.13  0.89340
## in_school_1996      -4.02e-01   1.14e-01   -3.52  0.00043 ***
## month2               1.07e+00   2.79e-01    3.82  0.00013 ***
## month3               1.58e+00   2.66e-01    5.92  3.1e-09 ***
## month4               3.58e-01   3.13e-01    1.14  0.25341
## month5               1.53e+00   2.65e-01    5.75  8.8e-09 ***
## month6               8.16e-01   2.86e-01    2.85  0.00437 **
## month7               8.78e-01   2.85e-01    3.08  0.00204 **
```

```
## month8              -3.88e-01   3.78e-01   -1.03  0.30492
## month9              -9.25e-01   4.50e-01   -2.06  0.03976 *
## month10             -6.70e-01   4.13e-01   -1.62  0.10504
## month11             -3.76e-01   3.78e-01   -0.99  0.32016
## month12              9.20e-01   2.88e-01    3.20  0.00139 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 5036.9  on 42645  degrees of freedom
## Residual deviance: 4666.9  on 42619  degrees of freedom
##   (3354 observations deleted due to missingness)
## AIC: 4721
##
## Number of Fisher Scoring iterations: 8
```

```
(marr_fixed_agedecades_or <- data.frame(coef = coef(marr_fixed_agedecades),
    OR = round(exp(coef(marr_fixed_agedecades)), 4)))
```

```
##                            coef        OR
## (Intercept)          -1.516e+01    0.0000
## ethnicHillTibeto      1.713e-01    1.1868
## ethnicLowHindu        1.410e-02    1.0142
## ethnicNewar          -2.411e-01    0.7857
## ethnicTeraiTibeto    -9.868e-02    0.9060
## genderfemale          8.088e-01    2.2452
## agedecades            7.452e+00 1723.7341
## I(agedecades^2)      -1.453e+00    0.2339
## interp_logpercagveg   1.293e-01    1.1381
## SCHLFT_1996           1.204e-02    1.0121
## HLTHFT_1996          -1.142e-03    0.9989
## BUSFT_1996            4.502e-03    1.0045
## MARFT_1996           -6.626e-04    0.9993
## EMPFT_1996            2.801e-03    1.0028
## schooling_yrs        -2.706e-03    0.9973
## in_school_1996       -4.025e-01    0.6687
## month2                1.066e+00    2.9038
## month3                1.578e+00    4.8469
## month4                3.579e-01    1.4303
## month5                1.527e+00    4.6028
## month6                8.158e-01    2.2610
## month7                8.776e-01    2.4051
## month8               -3.879e-01    0.6785
## month9               -9.250e-01    0.3965
## month10              -6.697e-01    0.5118
## month11              -3.759e-01    0.6867
## month12               9.202e-01    2.5098
```

```
write.csv(marr_fixed_agedecades_or, file = "models/marr_fixed_agedecades_odds.csv")
```

Mixed-effects model - random intercept at neighborhood level

```
(marr_2level <- glmer(marit ~ ethnic + gender + agedecades + I(agedecades^2) +
    interp_logpercagveg + interp_logpercagveg + SCHLFT_1996 + HLTHFT_1996 +
    BUSFT_1996 + MARFT_1996 + EMPFT_1996 + schooling_yrs + in_school_1996 +
    month + (1 | originalNBH), data = marit_long, family = binomial))
```

```
## Generalized linear mixed model fit by the Laplace approximation
## Formula: marit ~ ethnic + gender + agedecades + I(agedecades^2) + interp_logpercagveg +      interp_logpercagveg + SCHLFT_1996 + HLTHFT_1996 + BUSFT_1996 +      MARFT_1996 + EMPFT_1996 + schooling_yrs + in_school_1996 +      month + (1 | originalNBH)
##    Data: marit_long
##   AIC  BIC logLik deviance
##  4714 4956  -2329     4658
## Random effects:
##  Groups      Name        Variance Std.Dev.
##  originalNBH (Intercept) 0.124    0.352
## Number of obs: 42646, groups: originalNBH, 142
##
## Fixed effects:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -1.53e+01   2.80e+00   -5.47  4.6e-08 ***
## ethnicHillTibeto     1.65e-01   1.70e-01    0.97  0.33179
## ethnicLowHindu       6.04e-02   2.12e-01    0.29  0.77520
## ethnicNewar         -2.79e-01   2.19e-01   -1.27  0.20359
## ethnicTeraiTibeto   -9.38e-02   1.78e-01   -0.53  0.59878
## genderfemale         8.85e-01   1.07e-01    8.27  < 2e-16 ***
## agedecades           7.30e+00   2.64e+00    2.77  0.00567 **
## I(agedecades^2)     -1.36e+00   6.28e-01   -2.17  0.02968 *
## interp_logpercagveg  1.34e-01   8.04e-02    1.67  0.09462 .
## SCHLFT_1996          8.87e-03   9.90e-03    0.90  0.37053
## HLTHFT_1996         -2.66e-03   3.95e-03   -0.67  0.49979
## BUSFT_1996           5.17e-03   5.11e-03    1.01  0.31126
## MARFT_1996          -1.43e-03   4.01e-03   -0.36  0.72070
## EMPFT_1996           5.78e-03   3.34e-03    1.73  0.08329 .
## schooling_yrs       -6.95e-04   2.19e-02   -0.03  0.97471
## in_school_1996      -4.05e-01   1.21e-01   -3.34  0.00084 ***
## month2               1.07e+00   2.83e-01    3.77  0.00016 ***
## month3               1.58e+00   2.70e-01    5.87  4.5e-09 ***
## month4               3.64e-01   3.18e-01    1.15  0.25133
## month5               1.51e+00   2.69e-01    5.63  1.8e-08 ***
## month6               8.07e-01   2.90e-01    2.78  0.00543 **
## month7               8.71e-01   2.88e-01    3.02  0.00253 **
## month8              -3.93e-01   3.83e-01   -1.02  0.30572
## month9              -9.30e-01   4.56e-01   -2.04  0.04161 *
## month10             -6.74e-01   4.19e-01   -1.61  0.10792
## month11             -3.79e-01   3.83e-01   -0.99  0.32273
## month12              9.19e-01   2.92e-01    3.15  0.00164 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) ethnHT ethnLH ethncN ethnTT gndrfm agdcds I(g^2) intrp_
## ethncHllTbt -0.043
## ethnicLwHnd -0.029  0.198
## ethnicNewar -0.038  0.175  0.124
## ethnicTrTbt -0.018  0.229  0.259  0.125
## genderfemal -0.060  0.104  0.096 -0.054  0.047
## agedecades  -0.984  0.018  0.001  0.008 -0.005  0.013
## I(agdcds^2)  0.975 -0.017 -0.001 -0.012 -0.002 -0.005 -0.997
## intrp_lgprc -0.117 -0.004  0.017  0.197 -0.010  0.014  0.005 -0.006
## SCHLFT_1996 -0.037 -0.046 -0.055  0.026 -0.130 -0.001  0.016 -0.017  0.037
## HLTHFT_1996  0.000  0.148  0.030  0.147 -0.005  0.010  0.002 -0.003 -0.125
## BUSFT_1996   0.000  0.094  0.001 -0.033 -0.077  0.021  0.002  0.001 -0.109
## MARFT_1996  -0.009 -0.028  0.050 -0.023  0.164  0.026  0.003 -0.002 -0.031
## EMPFT_1996  -0.015 -0.108 -0.018 -0.006 -0.087 -0.002  0.013 -0.011 -0.104
## scholng_yrs -0.031  0.111  0.223  0.002  0.347  0.266 -0.017  0.000  0.042
## in_sch_1996 -0.033  0.062  0.041  0.003  0.051 -0.096  0.019 -0.007 -0.050
## month2      -0.105  0.001 -0.001 -0.001 -0.002  0.000  0.027 -0.025 -0.001
## month3      -0.112  0.000 -0.001 -0.002 -0.002  0.002  0.030 -0.027  0.000
## month4      -0.095  0.000  0.000 -0.001 -0.001  0.002  0.026 -0.023  0.000
## month5      -0.098  0.000  0.000  0.003  0.005 -0.003  0.020 -0.022  0.001
## month6      -0.092 -0.001 -0.001  0.002  0.004 -0.003  0.019 -0.021  0.001
## month7      -0.092 -0.001  0.000  0.001  0.002 -0.002  0.019 -0.021  0.001
## month8      -0.056 -0.002 -0.001  0.000  0.000 -0.002  0.000  0.000 -0.001
## month9      -0.047 -0.002 -0.001  0.000  0.000 -0.002  0.000  0.000 -0.001
## month10     -0.052 -0.001 -0.001  0.000  0.000 -0.002  0.000  0.000  0.000
## month11     -0.056 -0.001 -0.001  0.000  0.000 -0.001  0.000  0.000  0.000
## month12     -0.074  0.000 -0.001  0.000  0.000  0.000  0.000  0.000  0.000
##             SCHLFT HLTHFT BUSFT_ MARFT_ EMPFT_ schln_ i__199 month2 month3
## ethncHllTbt
## ethnicLwHnd
## ethnicNewar
## ethnicTrTbt
## genderfemal
## agedecades
## I(agdcds^2)
## intrp_lgprc
## SCHLFT_1996
## HLTHFT_1996 -0.126
## BUSFT_1996  -0.189 -0.235
## MARFT_1996  -0.065 -0.118 -0.245
## EMPFT_1996  -0.070 -0.218 -0.037 -0.227
## scholng_yrs -0.011  0.016  0.021  0.042  0.060
## in_sch_1996 -0.026 -0.070  0.058  0.071  0.016 -0.357
## month2      -0.001  0.000  0.001  0.001 -0.001 -0.009  0.010
## month3      -0.001  0.000  0.002  0.001 -0.001 -0.010  0.009  0.799
## month4      -0.001  0.000  0.002  0.001 -0.002 -0.008  0.008  0.679  0.711
## month5       0.001  0.000  0.000 -0.001 -0.003  0.005 -0.003  0.800  0.838
## month6       0.000  0.000  0.000 -0.002 -0.001  0.006 -0.004  0.741  0.777
## month7       0.000  0.000  0.000 -0.002  0.000  0.005 -0.005  0.746  0.781
## month8      -0.001  0.000  0.000  0.000  0.000 -0.001  0.002  0.561  0.588
## month9      -0.001  0.000  0.000  0.000  0.000 -0.001  0.001  0.472  0.494
## month10     -0.001  0.000  0.000  0.000  0.000 -0.001  0.001  0.514  0.538
## month11     -0.001  0.000  0.000  0.000  0.000 -0.001  0.001  0.561  0.588
## month12      0.000  0.000  0.001  0.000  0.000  0.000  0.000  0.737  0.772
##             month4 month5 month6 month7 month8 month9 mnth10 mnth11
## ethncHllTbt
## ethnicLwHnd
## ethnicNewar
## ethnicTrTbt
## genderfemal
## agedecades
## I(agdcds^2)
## intrp_lgprc
## SCHLFT_1996
## HLTHFT_1996
## BUSFT_1996
## MARFT_1996
## EMPFT_1996
## scholng_yrs
## in_sch_1996
## month2
## month3
## month4
## month5       0.712
## month6       0.660  0.781
## month7       0.664  0.786  0.729
## month8       0.500  0.590  0.547  0.551
## month9       0.420  0.496  0.460  0.463  0.348
## month10      0.457  0.540  0.501  0.504  0.379  0.318
## month11      0.500  0.590  0.547  0.551  0.414  0.348  0.379
## month12      0.657  0.775  0.719  0.723  0.544  0.457  0.498  0.544
```

```
(marr_2level_or <- data.frame(coef = fixef(marr_2level), OR = round(exp(fixef(marr_2level)),
    4)))
```

```
##                          coef       OR
## (Intercept)        -1.530e+01   0.0000
## ethnicHillTibeto    1.650e-01   1.1794
## ethnicLowHindu      6.040e-02   1.0623
## ethnicNewar        -2.787e-01   0.7568
```

```
## ethnicTeraiTibeto   -9.378e-02    0.9105
## genderfemale         8.853e-01    2.4236
## agedecades           7.301e+00 1481.2274
## I(agedecades^2)     -1.365e+00    0.2555
## interp_logpercagveg  1.343e-01    1.1438
## SCHLFT_1996          8.866e-03    1.0089
## HLTHFT_1996         -2.664e-03    0.9973
## BUSFT_1996           5.170e-03    1.0052
## MARFT_1996          -1.432e-03    0.9986
## EMPFT_1996           5.780e-03    1.0058
## schooling_yrs       -6.952e-04    0.9993
## in_school_1996      -4.053e-01    0.6668
## month2               1.068e+00    2.9090
## month3               1.584e+00    4.8735
## month4               3.644e-01    1.4397
## month5               1.515e+00    4.5491
## month6               8.067e-01    2.2405
## month7               8.709e-01    2.3891
## month8              -3.927e-01    0.6753
## month9              -9.296e-01    0.3947
## month10             -6.735e-01    0.5099
## month11             -3.791e-01    0.6845
## month12              9.190e-01    2.5067
```

```
save(marr_2level, file = "models/marr_2level.Rdata")
write.csv(marr_2level_or, file = "models/marr_2level_odds.csv")
```

Mixed-effects model - random intercepts at individual and neighborhood levels

```
(marr_3level <- glmer(marit ~ ethnic + gender + agedecades + I(agedecades^2) +
    interp_logpercagveg + SCHLFT_1996 + HLTHFT_1996 + BUSFT_1996 + MARFT_1996 +
    EMPFT_1996 + schooling_yrs + in_school_1996 + month + (1 | respid) + (1 |
    originalNBH), data = marit_long, family = binomial))
```

```
## Generalized linear mixed model fit by the Laplace approximation
## Formula: marit ~ ethnic + gender + agedecades + I(agedecades^2) + interp_logpercagveg +      SCHLFT_1996 + HLTHFT_1996 + BUSFT_1996 + MARFT_1996 + EMPFT_1996 +      schooling_yrs + in_school_1996 + month + (1 | respid) + (1 |      originalNBH)
##    Data: marit_long
##   AIC  BIC logLik deviance
##  4701 4952  -2322     4643
## Random effects:
##  Groups      Name        Variance Std.Dev.
##  respid      (Intercept) 1.0776   1.038
##  originalNBH (Intercept) 0.0814   0.285
## Number of obs: 42646, groups: respid, 723; originalNBH, 142
##
## Fixed effects:
##                     Estimate Std. Error z value Pr(>|z|)
## (Intercept)        -1.91e+01   3.24e+00   -5.90  3.7e-09 ***
## ethnicHillTibeto    2.17e-01   2.21e-01    0.98  0.32531
## ethnicLowHindu      2.00e-02   2.81e-01    0.07  0.94310
## ethnicNewar        -4.65e-01   2.89e-01   -1.61  0.10805
## ethnicTeraiTibeto  -8.34e-02   2.22e-01   -0.38  0.70728
## genderfemale        1.19e+00   1.45e-01    8.24  < 2e-16 ***
## agedecades          9.57e+00   3.04e+00    3.15  0.00163 **
## I(agedecades^2)    -1.59e+00   7.20e-01   -2.21  0.02735 *
## interp_logpercagveg  1.58e-01   9.94e-02    1.59  0.11106
## SCHLFT_1996         1.58e-02   1.22e-02    1.29  0.19637
## HLTHFT_1996        -3.12e-03   4.89e-03   -0.64  0.52290
## BUSFT_1996          5.31e-03   6.40e-03    0.83  0.40696
## MARFT_1996         -5.51e-04   4.98e-03   -0.11  0.91183
## EMPFT_1996          5.85e-03   4.10e-03    1.43  0.15334
## schooling_yrs      -3.71e-02   3.03e-02   -1.23  0.22031
## in_school_1996     -4.32e-01   1.62e-01   -2.66  0.00780 **
## month2              1.07e+00   3.01e-01    3.55  0.00039 ***
## month3              1.61e+00   2.88e-01    5.60  2.2e-08 ***
## month4              4.03e-01   3.39e-01    1.19  0.23462
## month5              1.44e+00   2.87e-01    5.04  4.8e-07 ***
## month6              7.52e-01   3.09e-01    2.43  0.01499 *
## month7              8.33e-01   3.07e-01    2.71  0.00670 **
## month8             -4.22e-01   4.09e-01   -1.03  0.30147
## month9             -9.57e-01   4.87e-01   -1.97  0.04927 *
## month10            -6.98e-01   4.47e-01   -1.56  0.11804
## month11            -4.00e-01   4.09e-01   -0.98  0.32773
## month12             9.10e-01   3.11e-01    2.93  0.00340 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) ethnHT ethnLH ethncN ethnTT gndrfm agdcds I(g^2) intrp_
## ethncHllTbt -0.069
## ethnicLwHnd -0.047  0.200
## ethnicNewar -0.048  0.168  0.122
## ethnicTrTbt -0.029  0.235  0.263  0.123
## genderfemal -0.108  0.114  0.101 -0.054  0.084
## agedecades  -0.981  0.040  0.010  0.009 -0.001  0.052
## I(agdcds^2)  0.972 -0.038 -0.010 -0.014 -0.004 -0.039 -0.997
## intrp_lgprc -0.131  0.000  0.025  0.235 -0.010  0.015  0.007 -0.006
## SCHLFT_1996 -0.045 -0.035 -0.052  0.014 -0.137  0.018  0.021 -0.020  0.031
## HLTHFT_1996  0.000  0.157  0.037  0.143  0.014  0.008  0.002 -0.003 -0.118
## BUSFT_1996  -0.011  0.086 -0.001  0.001 -0.097  0.027  0.011 -0.009 -0.090
## MARFT_1996  -0.005 -0.056  0.046 -0.048  0.148  0.028  0.001  0.001 -0.033
```

```
## EMPFT_1996  -0.029 -0.107  0.006  0.004 -0.054  0.001  0.022 -0.020 -0.095
## scholng_yrs -0.034  0.125  0.244  0.020  0.336  0.241 -0.028  0.012  0.041
## in_sch_1996 -0.031  0.049  0.064  0.002  0.055 -0.085  0.015 -0.007 -0.041
## month2      -0.098  0.001  0.001  0.000 -0.001  0.000  0.026 -0.023  0.000
## month3      -0.105  0.000  0.001 -0.001 -0.001  0.002  0.029 -0.027  0.001
## month4      -0.091  0.001  0.001 -0.001 -0.001  0.003  0.026 -0.023  0.001
## month5      -0.090  0.000  0.001  0.004  0.005 -0.008  0.019 -0.022  0.000
## month6      -0.085 -0.001 -0.001  0.003  0.004 -0.006  0.019 -0.022  0.000
## month7      -0.086 -0.002  0.000  0.002  0.002 -0.004  0.019 -0.022  0.000
## month8      -0.052 -0.003 -0.001  0.000  0.000 -0.002  0.000  0.000 -0.001
## month9      -0.043 -0.002 -0.001  0.000  0.000 -0.002  0.000  0.000 -0.001
## month10     -0.047 -0.002 -0.001  0.000  0.000 -0.002  0.000  0.000 -0.001
## month11     -0.051 -0.001 -0.001  0.000  0.000 -0.002  0.000  0.000  0.000
## month12     -0.068  0.000 -0.001  0.000  0.000 -0.001 -0.001  0.001 -0.001
##             SCHLFT HLTHFT BUSFT_ MARFT_ EMPFT_ schln_ i__199 month2 month3
## ethncHllTbt
## ethnicLwHnd
## ethnicNewar
## ethnicTrTbt
## genderfemal
## agedecades
## I(agdcds^2)
## intrp_lgprc
## SCHLFT_1996
## HLTHFT_1996 -0.118
## BUSFT_1996  -0.182 -0.246
## MARFT_1996  -0.073 -0.127 -0.276
## EMPFT_1996  -0.075 -0.219 -0.032 -0.215
## scholng_yrs -0.010  0.011  0.039  0.015  0.085
## in_sch_1996 -0.023 -0.050  0.023  0.077  0.033 -0.329
## month2      -0.002  0.000  0.001  0.002 -0.001 -0.010  0.011
## month3      -0.001  0.000  0.001  0.002 -0.001 -0.010  0.010  0.799
## month4       0.000  0.001  0.001  0.001 -0.002 -0.009  0.009  0.678  0.711
## month5      -0.002  0.001  0.000 -0.001 -0.005  0.005 -0.001  0.799  0.838
## month6      -0.002  0.001  0.000 -0.002 -0.002  0.005 -0.002  0.741  0.777
## month7      -0.002  0.001  0.001 -0.002  0.000  0.005 -0.003  0.745  0.781
## month8      -0.002  0.000  0.000 -0.001  0.000  0.000  0.002  0.561  0.588
## month9      -0.001  0.000  0.000  0.000  0.000 -0.001  0.002  0.471  0.494
## month10     -0.001  0.000  0.000  0.000 -0.001  0.000  0.001  0.513  0.538
## month11     -0.001  0.000  0.000 -0.001 -0.001  0.000  0.002  0.561  0.588
## month12     -0.001  0.000  0.001  0.000  0.000  0.000  0.001  0.737  0.773
##             month4 month5 month6 month7 month8 month9 mnth10 mnth11
## ethncHllTbt
## ethnicLwHnd
## ethnicNewar
## ethnicTrTbt
## genderfemal
## agedecades
## I(agdcds^2)
## intrp_lgprc
## SCHLFT_1996
## HLTHFT_1996
## BUSFT_1996
## MARFT_1996
## EMPFT_1996
## scholng_yrs
## in_sch_1996
## month2
## month3
## month4
## month5       0.711
## month6       0.659  0.782
## month7       0.663  0.786  0.729
## month8       0.499  0.590  0.547  0.550
## month9       0.419  0.496  0.459  0.462  0.348
## month10      0.456  0.540  0.500  0.504  0.379  0.318
## month11      0.499  0.590  0.547  0.550  0.414  0.348  0.379
## month12      0.656  0.776  0.719  0.724  0.544  0.457  0.498  0.544
```

```
save(marr_3level, file = "models/marr_3level.Rdata")
(marr_3level_or <- data.frame(coef = fixef(marr_3level), OR = round(exp(fixef(marr_3level)),
    4)))
```

```
##                            coef        OR
## (Intercept)          -19.113875 0.000e+00
## ethnicHillTibeto       0.217489 1.243e+00
## ethnicLowHindu         0.020035 1.020e+00
## ethnicNewar           -0.465178 6.280e-01
## ethnicTeraiTibeto     -0.083359 9.200e-01
## genderfemale           1.193235 3.298e+00
## agedecades             9.570212 1.433e+04
## I(agedecades^2)       -1.589726 2.040e-01
## interp_logpercagveg    0.158397 1.172e+00
## SCHLFT_1996            0.015787 1.016e+00
## HLTHFT_1996           -0.003122 9.969e-01
## BUSFT_1996             0.005310 1.005e+00
## MARFT_1996            -0.000551 9.994e-01
## EMPFT_1996             0.005852 1.006e+00
## schooling_yrs         -0.037138 9.635e-01
## in_school_1996        -0.431713 6.494e-01
## month2                 1.068951 2.912e+00
## month3                 1.610188 5.004e+00
## month4                 0.402727 1.496e+00
## month5                 1.443200 4.234e+00
## month6                 0.752179 2.122e+00
## month7                 0.833191 2.301e+00
## month8                -0.422263 6.556e-01
## month9                -0.956711 3.842e-01
## month10               -0.698179 4.975e-01
## month11               -0.399912 6.704e-01
## month12                0.910069 2.485e+00
```

```
write.csv(marr_3level_or, file = "models/marr_3level_odds.csv")
```

Conclusions

See below for comparison of the three models:

Model overview

Model	AIC	Log Likelihood
Fixed	4720.8578	-2333.4289
2-level (random int. at NBH level)	4713.7023	-2328.8512
3-level (random int. at resp and NBH level)	4701.2713	-2321.6356