

HW#8

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```
library(ggplot2) # for plots
library(magrittr) # for `%>%` operator
library(here)
library(readxl) # for reading excel files
library(modelsummary) # for summarizing data
library(rstan)
rstan_options(auto_write = TRUE) # save compiled STAN object
options(mc.cores = 2) # use two cores
library(posterior)
library(bayesplot)
theme_set(theme_classic() +
  theme(panel.grid.major.y = element_line(color = "grey92")))
library(psych)
library(tidyverse)
library(readr)
library(lmerTest)
library(brms)
```

Research Question

Can endorsement of six moral values predict the collective nostalgia proneness across 19 different cultures?

Variables

- `profevaluation` : evaluation rating of the instructor: 1 (very unsatisfactory) to 5 (excellent)
- `nonenglish` : 1 = non-native English speakers, 0 = native-English speakers

Import Data

```

nos_source_d = read_csv("19 cultures.csv")

nos_d = nos_source_d %>% select(
  CARE_tot,EQUALITY_tot,
  PROPORTIONALITY_tot,
  LOYALTY_tot,AUTHORITY_tot,
  PURITY_tot,Nostalgia,
  porient_1,age,religiosity_1,
  starts_with(c("CoNos")),country
)%>%
  mutate(
    C_Nostalgia = ((CoNos1+CoNos2+CoNos3+CoNos4)/4),
    moral_Ind = (CARE_tot+EQUALITY_tot+PROPORTIONALITY_tot)/3,
    moral_Group = (LOYALTY_tot+AUTHORITY_tot+PURITY_tot)/3,
    mean_Care = mean(CARE_tot),
    mean_Equality = mean(EQUALITY_tot),
    mean_Propotionality = mean(PROPORTIONALITY_tot),
    mean_Loyalty = mean(LOYALTY_tot),
    mean_Authority = mean(AUTHORITY_tot),
    mean_Purity = mean(PURITY_tot),
    mean_Age = mean(age,na.rm=TRUE),
    mean_P_Nostalgia = mean(Nostalgia,na.rm=TRUE)
  )%>%
  rename(
    Care = CARE_tot,
    Equality = EQUALITY_tot,
    Propotionality = PROPORTIONALITY_tot,
    Loyalty = LOYALTY_tot,
    Authority = AUTHORITY_tot,
    Purity = PURITY_tot,
    P_Nostalgia = Nostalgia,
    Religiosity = religiosity_1,
    Conservatism = porient_1,
    Age = age
  )

```

Variable Summary

```

#Sample size in each country
count(nos_d, country)

```

```

## # A tibble: 19 x 2
##   country      n
##   <chr>      <int>
## 1 Argentina   205
## 2 Belgium    205
## 3 Chile       205
## 4 Columbia   205
## 5 Egypt      205
## 6 France     206
## 7 Ireland    205
## 8 Japan      207
## 9 Kenya    205
## 10 Mexico     206
## 11 Morocco   205
## 12 New Zealand 205
## 13 Nigeria    205
## 14 Peru       205
## 15 Russia     206
## 16 Saudi Arabia 207
## 17 South Africa 205
## 18 Switzerland 205
## 19 UAE        205

```

```
#summarizing data in each country
```

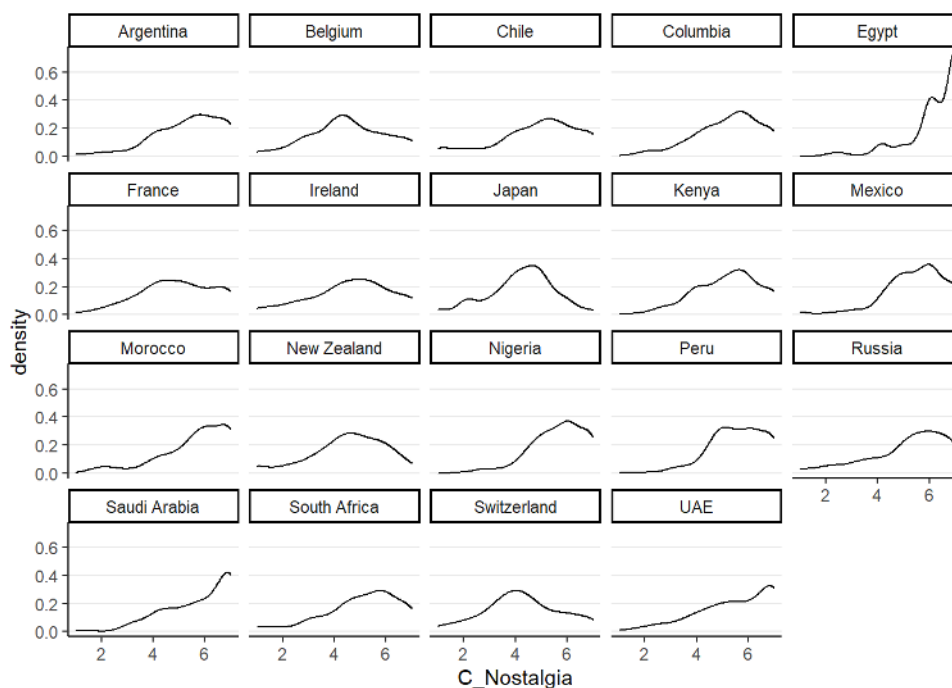
```
nos_d %>%
  group_by(country) %>%
  summarise(mean = mean(C_Nostalgia, na.rm = T),
            SD = sd(C_Nostalgia, na.rm = T),
            Min = min(C_Nostalgia, na.rm = T),
            Max = max(C_Nostalgia, na.rm = T),
            )%>%
  mutate_if(is.numeric, ~round(., 2)) %>%
  print(n = 50)
```

```
## # A tibble: 19 x 5
##   country      mean    SD   Min   Max
##   <chr>      <dbl> <dbl> <dbl> <dbl>
## 1 Argentina  5.37  1.32   1     7
## 2 Belgium    4.51  1.48   1     7
## 3 Chile      4.85  1.63   1     7
## 4 Columbia   5.24  1.29   1     7
## 5 Egypt      6.19  1.04   2     7
## 6 France     4.89  1.44   1     7
## 7 Ireland    4.61  1.57   1     7
## 8 Japan      4.21  1.29   1     7
## 9 Kenya     5.19  1.24  1.25   7
## 10 Mexico     5.45  1.18   1     7
## 11 Morocco    5.63  1.33   1.5    7
## 12 New Zealand 4.54  1.43   1     7
## 13 Nigeria    5.64  1.04   2     7
## 14 Peru       5.57  1.08   1     7
## 15 Russia     5.2    1.53   1     7
## 16 Saudi Arabia 5.77  1.28   1     7
## 17 South Africa 5.07  1.44   1     7
## 18 Switzerland 4.26  1.47   1     7
## 19 UAE        5.47  1.45   1     7
```

```
# Look at distribution by country
```

```
nos_d %>%
  ggplot(aes(C_Nostalgia)) +
  geom_density() +
  facet_wrap(~country)
```

```
## Warning: Removed 5 rows containing non-finite values (stat_density).
```



Model

Let Y = profevaluation, G = nonenglish

Model: \$\$

Individual level:

$$\mathbf{C_Nostalgia}_{ij} \sim \mathcal{N}(\mu_{ij}, \sigma)$$

$$\mu_{ij} =$$

$$\beta_{0j} +$$

$$\beta_{1j}\mathbf{Care}_{ij} +$$

$$\beta_{2j}\mathbf{Equality}_{ij} +$$

$$\beta_{3j}\mathbf{Propotionality}_{ij} +$$

$$\beta_{4j}\mathbf{Loyalty}_{ij} +$$

$$\beta_{5j}\mathbf{Authority}_{ij} +$$

$$\beta_{6j}\mathbf{Purity}_{ij} +$$

$$\beta_{7j}\mathbf{P_Nostalgia}_{ij} +$$

$$\beta_{8j}\mathbf{Religiosity}_{ij} +$$

$$\beta_{9j}\mathbf{Conservatism}_{ij} +$$

$$\beta_{10j}\mathbf{Age}_{ij}$$

County level:

$$\beta_{0j} \sim \mathcal{N}(\mu^{[\beta_0]}, \tau^{[\beta_0]})$$

\$\$

Prior:

Running brms

We used 4 chains, each with 4,000 iterations (first 2,000 as warm-ups).

```
m1_fit=readRDS(file = "my_data.rds")
summary(m1_fit)
```

```

## Family: gaussian
## Links: mu = identity; sigma = identity
## Formula: C_Nostalgia ~ 1 + Care + Equality + Propotionality + Loyalty + Authority + Purity + +Conservatism + P_Nostalgia
+ Age + mean_Care + mean_Equality + mean_Propotionality + mean_Loyalty + mean_Authority + mean_Purity + mean_P_Nostalgia + m
ean_Age + (1 | country)
## Data: nos_d (Number of observations: 3680)
## Draws: 4 chains, each with iter = 4000; warmup = 2000; thin = 1;
## total post-warmup draws = 8000
##
## Group-Level Effects:
## ~country (Number of levels: 19)
## Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept) 0.31 0.06 0.22 0.45 1.00 1409 2633
##
## Population-Level Effects:
## Estimate Est.Error
## Intercept -6135891535363441.00 19943302765414832.00
## Care -0.04 0.03
## Equality 0.04 0.02
## Propotionality -0.03 0.03
## Loyalty 0.29 0.03
## Authority 0.40 0.04
## Purity 0.12 0.03
## Conservatism 0.03 0.01
## P_Nostalgia 0.38 0.01
## Age -0.00 0.00
## mean_Care 141822435261972.25 672806573107786.25
## mean_Equality -23213199303772.18 972574992923735.12
## mean_Propotionality -474237305644288.75 1162882006414636.50
## mean_Loyalty 1339716146715075.00 1613066160319512.50
## mean_Authority -7371477570737.66 2615706639725024.50
## mean_Purity -418348078510432.81 1201839504116819.50
## mean_P_Nostalgia 500576617974214.69 489885350392581.56
## mean_Age 43267138560574.63 197410202130227.88
## l-95% CI u-95% CI Rhat Bulk_ESS
## Intercept -45020159827702688.00 25198860588418864.00 2.43 5
## Care -0.10 0.02 1.00 8433
## Equality -0.00 0.08 1.00 7846
## Propotionality -0.09 0.04 1.00 7602
## Loyalty 0.23 0.35 1.00 6422
## Authority 0.33 0.48 1.00 5769
## Purity 0.06 0.17 1.00 7019
## Conservatism 0.01 0.04 1.00 9738
## P_Nostalgia 0.35 0.40 1.00 9863
## Age -0.00 0.00 1.00 10968
## mean_Care -1579511599534515.75 1565009840274948.00 1.56 8
## mean_Equality -2741802691552028.00 1304605151111614.50 1.91 6
## mean_Propotionality -3093728000404815.00 1448132170164927.00 1.88 6
## mean_Loyalty -1400963482761625.75 4363812405006119.00 2.13 5
## mean_Authority -4924696244579012.00 5546592480217804.00 2.82 5
## mean_Purity -3411620160541986.50 1938019405620595.25 2.03 5
## mean_P_Nostalgia -149269959690262.94 1733315154036284.75 1.61 7
## mean_Age -331527548173030.25 383844463386461.25 2.35 5
## Tail_ESS
## Intercept NA
## Care 6142
## Equality 6177
## Propotionality 6092
## Loyalty 6134
## Authority 6262
## Purity 6157
## Conservatism 5953
## P_Nostalgia 5346
## Age 5839
## mean_Care NA
## mean_Equality NA
## mean_Propotionality NA
## mean_Loyalty NA
## mean_Authority NA
## mean_Purity NA
## mean_P_Nostalgia NA
## mean_Age NA

```

```
##
## Family Specific Parameters:
##      Estimate Est.Error 1-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma      1.05      0.01   1.03   1.07 1.00   9768   6247
##
## Draws were sampled using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

Get priors:

```
get_prior(C_Nostalgia ~ 1 + Care+ Equality+ Propotionality
          + Loyalty+ Authority+ Purity+
          + Conservatism + P_Nostalgia + Age
          + mean_Care + mean_Equality
          + mean_Propotionality + mean_Loyalty
          + mean_Authority + mean_Purity
          + mean_P_Nostalgia + mean_Age
          + (1|country)
          ,

          family = gaussian(link = "identity"),
          data = nos_d)
```

```
## Warning: Rows containing NAs were excluded from the model.
```

Convergence check of MCMC

```
## No divergences to plot.
```

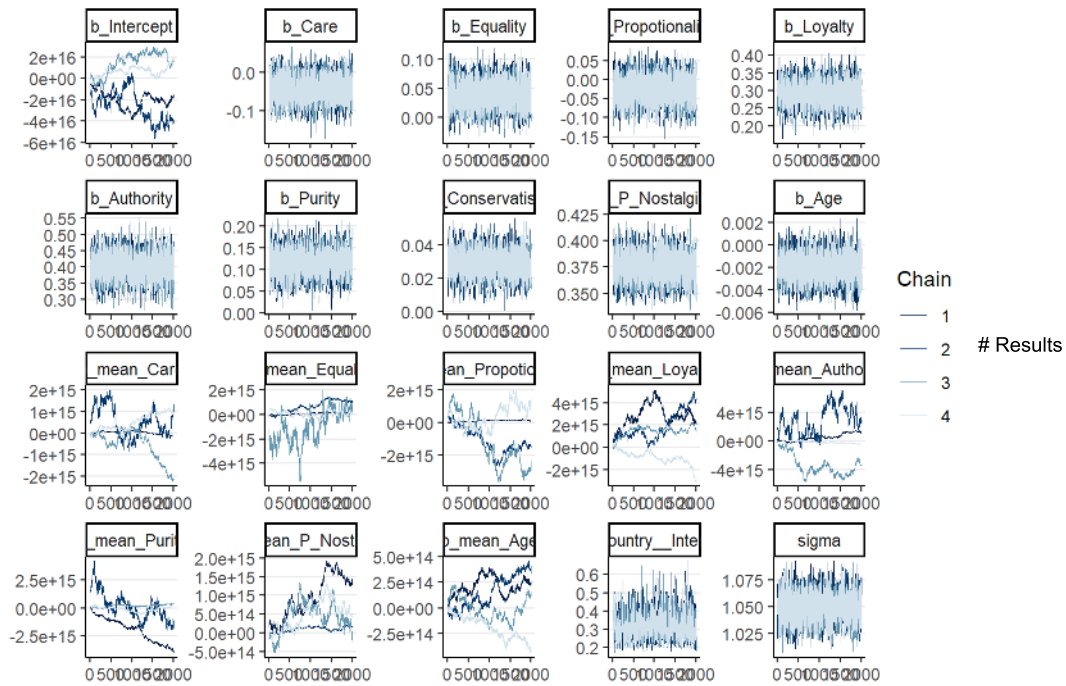


Table of coefficients

```
m1_fit %>%
  # Convert to `draws` object to work with the `posterior` package
  as_draws() %>%
  # Get summary
  summarize_draws() %>%
  # Use `knitr::kable()` for tabulation
  knitr::kable(digits = 2)
```

variable	mean	median	sd	mad	q5	q95	rhat	ess_bulk	es
b_Intercept	-6.135892e+15	-4.268493e+15	1.994330e+16	2.246563e+16	-3.969580e+16	2.372787e+16	2.43	4.89	
b_Care	-4.000000e-02	-4.000000e-02	3.000000e-02	3.000000e-02	-9.000000e-02	1.000000e-02	1.00	8432.99	61
b_Equality	4.000000e-02	4.000000e-02	2.000000e-02	2.000000e-02	0.000000e+00	8.000000e-02	1.00	7845.73	61
b_Propotionality	-3.000000e-02	-3.000000e-02	3.000000e-02	3.000000e-02	-8.000000e-02	3.000000e-02	1.00	7602.43	60
b_Loyalty	2.900000e-01	2.900000e-01	3.000000e-02	3.000000e-02	2.400000e-01	3.400000e-01	1.00	6422.16	61
b_Authority	4.000000e-01	4.000000e-01	4.000000e-02	4.000000e-02	3.400000e-01	4.600000e-01	1.00	5768.92	62
b_Purity	1.200000e-01	1.200000e-01	3.000000e-02	3.000000e-02	7.000000e-02	1.600000e-01	1.00	7018.63	61
b_Conservatism	3.000000e-02	3.000000e-02	1.000000e-02	1.000000e-02	2.000000e-02	4.000000e-02	1.00	9737.63	59
b_P_Nostalgia	3.800000e-01	3.800000e-01	1.000000e-02	1.000000e-02	3.600000e-01	4.000000e-01	1.00	9863.26	53
b_Age	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	1.00	10967.52	58
b_mean_Care	1.418224e+14	8.884616e+13	6.728066e+14	3.130974e+14	-1.119253e+15	1.286299e+15	1.56	7.82	
b_mean_Equality	-2.321320e+13	1.388712e+14	9.725750e+14	3.505750e+14	-2.236765e+15	1.238962e+15	1.91	6.27	
b_mean_Propotionality	-4.742373e+14	-4.825037e+13	1.162882e+15	8.735318e+14	-2.818101e+15	1.157375e+15	1.88	5.67	
b_mean_Loyalty	1.339716e+15	1.499474e+15	1.613066e+15	1.594513e+15	-1.226625e+15	4.113604e+15	2.13	5.18	
b_mean_Authority	-7.371478e+12	3.168752e+13	2.615707e+15	1.296361e+15	-4.665176e+15	4.773206e+15	2.82	4.66	
b_mean_Purity	-4.183481e+14	-4.582312e+13	1.201840e+15	4.989748e+14	-3.110012e+15	9.108577e+14	2.03	5.36	
b_mean_P_Nostalgia	5.005766e+14	3.987817e+14	4.898854e+14	4.557662e+14	-2.905459e+13	1.575792e+15	1.61	6.74	
b_mean_Age	4.326714e+13	3.627833e+13	1.974102e+14	2.140246e+14	-2.938724e+14	3.614772e+14	2.35	4.93	
sd_country__Intercept	3.100000e-01	3.100000e-01	6.000000e-02	6.000000e-02	2.300000e-01	4.300000e-01	1.00	1409.05	26
sigma	1.050000e+00	1.050000e+00	1.000000e-02	1.000000e-02	1.030000e+00	1.070000e+00	1.00	9767.84	62

variable	mean	median	sd	mad	q5	q95	rhat	ess_bulk	es
Intercept	5.680000e+00	5.230000e+00	5.920000e+00	2.870000e+00	-5.800000e-01	1.147000e+01	1.01	576.00	2
r_country[Argentina,Intercept]	4.600000e-01	4.600000e-01	1.000000e-01	1.000000e-01	2.900000e-01	6.400000e-01	1.00	1858.71	36
r_country[Belgium,Intercept]	-4.900000e-01	-4.900000e-01	1.000000e-01	1.000000e-01	-6.600000e-01	-3.200000e-01	1.00	1756.90	36
r_country[Chile,Intercept]	1.000000e-02	1.000000e-02	1.000000e-01	1.000000e-01	-1.600000e-01	1.800000e-01	1.00	1735.48	32
r_country[Columbia,Intercept]	2.700000e-01	2.700000e-01	1.100000e-01	1.000000e-01	1.000000e-01	4.400000e-01	1.00	1855.90	33
r_country[Egypt,Intercept]	0.000000e+00	0.000000e+00	1.000000e-01	1.000000e-01	-1.700000e-01	1.700000e-01	1.00	1827.85	38
r_country[France,Intercept]	-2.200000e-01	-2.200000e-01	1.000000e-01	1.000000e-01	-3.900000e-01	-6.000000e-02	1.00	1717.24	34
r_country[Ireland,Intercept]	-1.500000e-01	-1.500000e-01	1.000000e-01	1.000000e-01	-3.200000e-01	2.000000e-02	1.00	1742.52	37
r_country[Japan,Intercept]	1.600000e-01	1.600000e-01	1.100000e-01	1.100000e-01	-1.000000e-02	3.400000e-01	1.00	1936.30	33
r_country[Kenya,Intercept]	-1.400000e-01	-1.400000e-01	1.100000e-01	1.100000e-01	-3.200000e-01	4.000000e-02	1.00	1909.86	35
r_country[Mexico,Intercept]	4.000000e-01	4.000000e-01	1.000000e-01	1.000000e-01	2.300000e-01	5.700000e-01	1.00	1746.13	38
r_country[Morocco,Intercept]	-8.000000e-02	-8.000000e-02	1.000000e-01	1.000000e-01	-2.600000e-01	9.000000e-02	1.00	1890.27	37
r_country[New.Zealand,Intercept]	-1.500000e-01	-1.500000e-01	1.000000e-01	1.000000e-01	-3.200000e-01	2.000000e-02	1.00	1671.05	36
r_country[Nigeria,Intercept]	1.800000e-01	1.800000e-01	1.000000e-01	1.000000e-01	1.000000e-02	3.600000e-01	1.00	1906.10	38
r_country[Peru,Intercept]	4.600000e-01	4.600000e-01	1.000000e-01	1.000000e-01	2.900000e-01	6.300000e-01	1.00	1836.32	36
r_country[Russia,Intercept]	1.500000e-01	1.500000e-01	1.000000e-01	1.000000e-01	-2.000000e-02	3.200000e-01	1.00	1702.09	36
r_country[Saudi.Arabia,Intercept]	-6.000000e-02	-6.000000e-02	1.000000e-01	1.000000e-01	-2.300000e-01	1.100000e-01	1.00	1869.00	34
r_country[South.Africa,Intercept]	-8.000000e-02	-8.000000e-02	1.000000e-01	1.000000e-01	-2.500000e-01	9.000000e-02	1.00	1844.80	35
r_country[Switzerland,Intercept]	-5.300000e-01	-5.300000e-01	1.000000e-01	1.000000e-01	-7.000000e-01	-3.600000e-01	1.00	1806.46	34
r_country[UAE,Intercept]	-2.100000e-01	-2.100000e-01	1.000000e-01	1.000000e-01	-3.700000e-01	-4.000000e-02	1.00	1684.04	33
lp__	-5.433760e+03	-5.433470e+03	5.090000e+00	5.070000e+00	-5.442600e+03	-5.425980e+03	1.01	1393.27	24
z_1[1,1]	1.510000e+00	1.500000e+00	4.100000e-01	4.000000e-01	8.600000e-01	2.200000e+00	1.00	1746.08	31
z_1[1,2]	-1.620000e+00	-1.610000e+00	4.300000e-01	4.200000e-01	-2.350000e+00	-9.500000e-01	1.00	1480.56	32
z_1[1,3]	3.000000e-02	3.000000e-02	3.300000e-01	3.300000e-01	-5.100000e-01	5.700000e-01	1.00	1790.90	34
z_1[1,4]	8.800000e-01	8.700000e-01	3.600000e-01	3.600000e-01	3.000000e-01	1.490000e+00	1.00	1890.04	35
z_1[1,5]	0.000000e+00	0.000000e+00	3.400000e-01	3.400000e-01	-5.500000e-01	5.700000e-01	1.00	1865.46	38
z_1[1,6]	-7.400000e-01	-7.200000e-01	3.500000e-01	3.500000e-01	-1.340000e+00	-1.800000e-01	1.00	1619.89	33
z_1[1,7]	-5.000000e-01	-5.000000e-01	3.400000e-01	3.400000e-01	-1.090000e+00	5.000000e-02	1.00	1705.57	33
z_1[1,8]	5.400000e-01	5.300000e-01	3.600000e-01	3.500000e-01	-4.000000e-02	1.140000e+00	1.00	2047.75	35
z_1[1,9]	-4.500000e-01	-4.400000e-01	3.600000e-01	3.500000e-01	-1.040000e+00	1.200000e-01	1.00	1926.19	35
z_1[1,10]	1.300000e+00	1.290000e+00	3.900000e-01	3.800000e-01	6.800000e-01	1.960000e+00	1.00	1687.24	38
z_1[1,11]	-2.800000e-01	-2.700000e-01	3.400000e-01	3.400000e-01	-8.600000e-01	2.800000e-01	1.00	1929.11	36
z_1[1,12]	-4.900000e-01	-4.900000e-01	3.500000e-01	3.500000e-01	-1.080000e+00	6.000000e-02	1.00	1651.40	35
z_1[1,13]	6.000000e-01	5.900000e-01	3.500000e-01	3.400000e-01	4.000000e-02	1.190000e+00	1.00	1897.73	37
z_1[1,14]	1.500000e+00	1.490000e+00	4.100000e-01	4.000000e-01	8.600000e-01	2.190000e+00	1.00	1686.83	33
z_1[1,15]	5.000000e-01	4.900000e-01	3.400000e-01	3.400000e-01	-5.000000e-02	1.070000e+00	1.00	1727.87	36
z_1[1,16]	-1.800000e-01	-1.800000e-01	3.400000e-01	3.300000e-01	-7.500000e-01	3.700000e-01	1.00	1913.16	37
z_1[1,17]	-2.500000e-01	-2.500000e-01	3.400000e-01	3.400000e-01	-8.200000e-01	3.000000e-01	1.00	1807.51	36
z_1[1,18]	-1.740000e+00	-1.730000e+00	4.300000e-01	4.300000e-01	-2.490000e+00	-1.050000e+00	1.00	1439.09	29
z_1[1,19]	-6.800000e-01	-6.700000e-01	3.500000e-01	3.600000e-01	-1.270000e+00	-1.200000e-01	1.00	1602.49	31

Interpretations

We found evidence that loyalty, authority and purity can significantly predict collective nostalgia across 19 countries after controlling for age, personal nostalgia and age.