Religion and tolerance

In [131]:
```
import numpy as np
import pandas as pd
```

In [132]:
```
gss = pd.read_excel('/Users/antoshachekhonte/Downloads/GSS.XLSX')
```

In [133]:
```
gss.head()
```

Out[133]:

	YEAR	ID	WRKSTAT	HRS1	HRS2	EVWORK	WRKSLF	WRKGOVT	OCC10	PRESTG1
0	2016	1	1	50	-1	0	2	2	1020	60
1	2016	2	1	42	-1	0	2	2	8030	40
2	2016	3	5	-1	-1	1	2	2	7020	38
3	2016	4	2	30	-1	0	2	2	4600	35
4	2016	5	2	5	-1	0	2	2	4760	31

5 rows × 948 columns

Subsetting relevant variables

Explanatory variables:

1. God - respondent's belief in God
2. Savesoul - whether respondent has encouraged somebody to believe in Jesus
3. Reppersn - level of religiosity
4. Attend - frequency of religious service attendance
5. Fund - fundamentalism / liberalism of respondent's religion
6. Pray - prayer frequency
7. Polviews - political views
8. Sex
9. Educ
10. Sprel - spouse's religious preference
11. Spfund - fundamentalism of spouse
12. Bible - belief in bible

Target variables:

1. MARBLK - would you be in favor of having a close relation marry a black person
2. Homosex - permissibility of same-sex sexual relations

In [134]:
```
gss_sub = gss[['GOD', 'SAVESOUL', 'RELPERSN', 'ATTEND', 'FUND', \
               'PRAY', 'POLVIEWS', 'SEX', 'EDUC', 'SPFUND', \
               'BIBLE', 'MARBLK', 'HOMOSEX', 'AGE']]
```

In [135]:
```
gss_sub.head()
```

Out[135]:

	GOD	SAVESOUL	RELPERSN	ATTEND	FUND	PRAY	POLVIEWS	SEX	EDUC	SPFUN
0	2	2	4	0	3	6	4	1	16	3
1	8	2	4	0	3	6	2	1	12	0
2	6	2	1	7	2	1	6	1	16	2
3	6	2	2	6	2	3	4	2	12	2
4	1	2	4	0	3	6	3	2	18	3

In [136]:
```
gss_sub = gss_sub[(gss_sub['GOD'] != 8) & (gss_sub['GOD'] != 9)\
                  & (gss_sub['SAVESOUL'] != 8) & (gss_sub['SAVESOUL'] !=
 9)\
                  & (gss_sub['RELPERSN'] != 8) & (gss_sub['RELPERSN'] !=
 9)\
                  & (gss_sub['ATTEND'] != 8) & (gss_sub['ATTEND'] != 9)\
                  & (gss_sub['FUND'] != 9)\
                  & (gss_sub['PRAY'] != 8) & (gss_sub['PRAY'] != 9)\
                  & (gss_sub['POLVIEWS'] != 8) & (gss_sub['POLVIEWS'] !=
 9)\
                  & (gss_sub['EDUC'] != 98) & (gss_sub['PRAY'] != 99)\
                  & (gss_sub['SPFUND'] != 9) & (gss_sub['SPFUND'] != 0)\
                  & (gss_sub['BIBLE'] != 8) & (gss_sub['BIBLE'] != 9) &
(gss_sub['BIBLE'] != 4)\
                  & (gss_sub['MARBLK'] != 8) & (gss_sub['MARBLK'] != 9)]
```

In [137]:
```
gss_sub.shape
```

Out[137]: (964, 14)

In [138]:
```
# reverse coding
gss_sub.loc[gss_sub['HOMOSEX'] == 1, 'HOMOSEX_RECODED'] = 4
gss_sub.loc[gss_sub['HOMOSEX'] == 2, 'HOMOSEX_RECODED'] = 3
gss_sub.loc[gss_sub['HOMOSEX'] == 3, 'HOMOSEX_RECODED'] = 2
gss_sub.loc[gss_sub['HOMOSEX'] == 4, 'HOMOSEX_RECODED'] = 1
```

In [139]:
```
# reverse coding
gss_sub.loc[gss_sub['SAVESOUL'] == 1, 'SAVESOUL_RECODED'] = 2
gss_sub.loc[gss_sub['SAVESOUL'] == 2, 'SAVESOUL_RECODED'] = 1
```

In [140]:
```
# reverse coding
gss_sub.loc[gss_sub['RELPERSN'] == 1, 'RELPERSN_RECODED'] = 4
gss_sub.loc[gss_sub['RELPERSN'] == 2, 'RELPERSN_RECODED'] = 3
gss_sub.loc[gss_sub['RELPERSN'] == 3, 'RELPERSN_RECODED'] = 2
gss_sub.loc[gss_sub['RELPERSN'] == 4, 'RELPERSN_RECODED'] = 1
```

In [141]:
```
# reverse coding
gss_sub.loc[gss_sub['FUND'] == 1, 'FUND_RECODED'] = 3
gss_sub.loc[gss_sub['FUND'] == 2, 'FUND_RECODED'] = 2
gss_sub.loc[gss_sub['FUND'] == 3, 'FUND_RECODED'] = 1
```

In [142]:
```
# reverse coding
gss_sub.loc[gss_sub['PRAY'] == 1, 'PRAY_RECODED'] = 6
gss_sub.loc[gss_sub['PRAY'] == 2, 'PRAY_RECODED'] = 5
gss_sub.loc[gss_sub['PRAY'] == 3, 'PRAY_RECODED'] = 4
gss_sub.loc[gss_sub['PRAY'] == 4, 'PRAY_RECODED'] = 3
gss_sub.loc[gss_sub['PRAY'] == 5, 'PRAY_RECODED'] = 2
gss_sub.loc[gss_sub['PRAY'] == 6, 'PRAY_RECODED'] = 1
```

In [143]:
```
# reverse coding
gss_sub.loc[gss_sub['SPFUND'] == 1, 'SPFUND_RECODED'] = 3
gss_sub.loc[gss_sub['SPFUND'] == 2, 'SPFUND_RECODED'] = 2
gss_sub.loc[gss_sub['SPFUND'] == 3, 'SPFUND_RECODED'] = 1
```

In [144]:
```
# reverse coding
gss_sub.loc[gss_sub['BIBLE'] == 1, 'BIBLE_RECODED'] = 3
gss_sub.loc[gss_sub['BIBLE'] == 2, 'BIBLE_RECODED'] = 2
gss_sub.loc[gss_sub['BIBLE'] == 3, 'BIBLE_RECODED'] = 1
```

In [145]:
```
# creating duplicate for safety
gss_sub_dup = gss_sub
```

Hypothesis

There is a causal relationship between religiosity and tolerance.

Preliminary analysis

Let's start off by seeing how our explanatory variables correlate with the outcome variable.

In [146]:
```
# GOD
```

In [147]:
```
gss_sub.groupby('GOD').size()
```

Out[147]:
```
GOD
1     30
2     69
3    104
4     34
5    175
6    552
dtype: int64
```

In [148]:
```
gss_sub[gss_sub['MARBLK'] != 0].groupby('GOD').MARBLK.mean()
```

Out[148]:
```
GOD
1    2.888889
2    2.756098
3    2.535211
4    2.900000
5    2.862385
6    2.652174
Name: MARBLK, dtype: float64
```

In [149]:
```
gss_sub[gss_sub['HOMOSEX'] != 0].groupby('GOD').HOMOSEX_RECODED.mean()
```

Out[149]:
```
GOD
1    1.619048
2    1.580000
3    1.333333
4    1.625000
5    1.752294
6    2.804408
Name: HOMOSEX_RECODED, dtype: float64
```

In [150]:
```
# RELPERSN
```

In [151]:
```
gss_sub.groupby('RELPERSN_RECODED').size()
```

Out[151]:
```
RELPERSN_RECODED
1.0    190
2.0    210
3.0    407
4.0    157
dtype: int64
```

In [152]:
```
gss_sub[gss_sub['MARBLK'] != 0].groupby('RELPERSN_RECODED').MARBLK.mean
()
```

Out[152]:
```
RELPERSN_RECODED
1.0    2.569106
2.0    2.793893
3.0    2.735507
4.0    2.618557
Name: MARBLK, dtype: float64
```

In [153]:
```
gss_sub[gss_sub['HOMOSEX'] != 0].groupby('RELPERSN_RECODED').HOMOSEX_REC
ODED.mean()
```

Out[153]:
```
RELPERSN_RECODED
1.0    1.433071
2.0    1.822222
3.0    2.590734
4.0    3.174312
Name: HOMOSEX_RECODED, dtype: float64
```

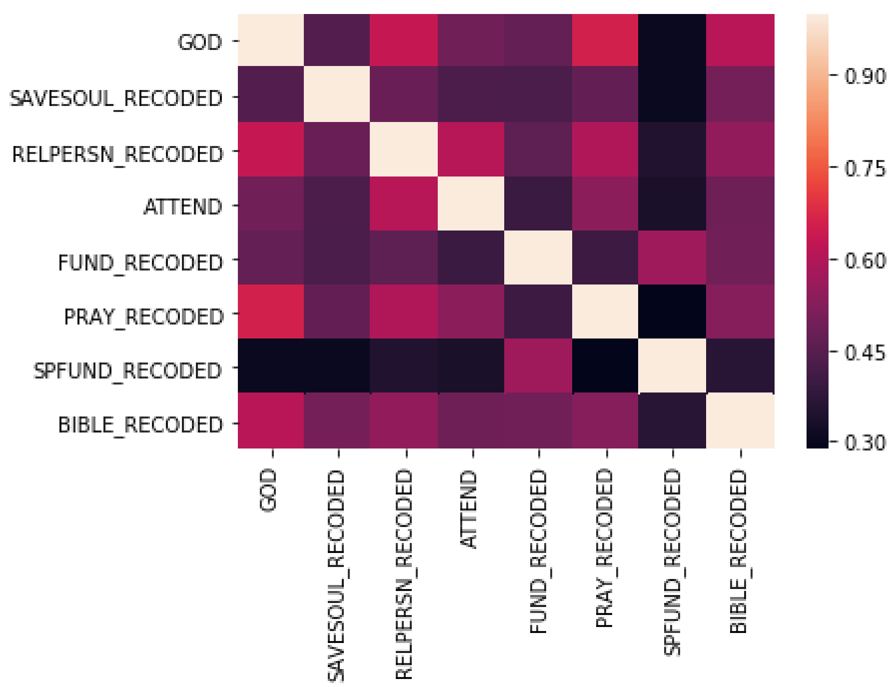
Building the explanatory variable

I shall attempt to build a measure of religiosity using the variables: GOD, SAVESOUL, RELPERSN, ATTEND, FUND, PRAY, SPREL, SPFUND, BIBLE

In [154]:
```
explanatory_var = gss_sub[['GOD', 'SAVESOUL_RECODED', 'RELPERSN_RECODED'
, 'ATTEND', 'FUND_RECODED', \
                              'PRAY_RECODED', 'SPFUND_RECODED', 'BIBLE_RECO
DED']]
```

In [155]:
```
%matplotlib inline
import seaborn as sns
corr = explanatory_var.corr()
sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns)
```

Out[155]: <matplotlib.axes._subplots.AxesSubplot at 0x1174fb518>



In [156]:
```
from sklearn.decomposition import FactorAnalysis
transformer = FactorAnalysis(n_components = 3, random_state = 0)
explanatory_var_transformed = transformer.fit_transform(explanatory_var)
explanatory_var_transformed.shape
```

Out[156]: (964, 3)

In [157]:
```
# what is the explained variance?
m = transformer.components_
n = transformer.noise_variance_
m1 = m**2
m2 = np.sum(m1, axis=1)
pvar1 = (100*m2[0])/np.sum(m2)
pvar2 = (100*m2[1])/np.sum(m2)
pvar3 = (100*m2[2])/np.sum(m2)
print('the variance explained by the first factor is', pvar1)
print('the variance explained by the second factor is', pvar2)
print('the variance explained by the third factor is', pvar3)
```

```
the variance explained by the first factor is 80.58588443437463
the variance explained by the second factor is 13.62823115983241
the variance explained by the third factor is 5.785884405792952
```

In [158]:
```
print('Total explained variance is', pvar1+pvar2+pvar3)
```

```
Total explained variance is 100.0
```

In [159]:
```
# adding this to the overall dataframe
gss_sub['FIRSTVAR'] = explanatory_var_transformed[:, 0]
gss_sub['SECONDVAR'] = explanatory_var_transformed[:, 1]
gss_sub['THIRDVAR'] = explanatory_var_transformed[:, 2]
```

In [160]:
```
transformer.components_[0, :]
```

Out[160]:
```
array([-1.12396264, -0.29621073, -0.76127251, -2.13735438, -0.46616938,
       -1.28718258, -0.3578076 , -0.50899615])
```

In [161]:
```
transformer.components_[1, :]
```

Out[161]:
```
array([-0.35831058, -0.06194621, -0.03310896,  1.09313828, -0.27553521,
       -0.15033214, -0.18344426, -0.14497503])
```

In [162]:
```
transformer.components_[2, :]
```

Out[162]:
```
array([-0.44909507,  0.00168552, -0.10722245,  0.24307689,  0.2640919 ,
       -0.43491402,  0.30871753, -0.04982478])
```

In [163]:
```
import scipy.stats
scipy.stats.describe(explanatory_var_transformed[:, 0])
```

Out[163]:
```
DescribeResult(nobs=964, minmax=(-1.5341857802485117, 2.04453941414954
2), mean=8.844930320665147e-17, variance=0.9292641506111441, skewness=
0.3845519752369101, kurtosis=-0.8761730358797837)
```

The primary factor ranges from a min of -1.53 to a max of 2.04 with a variance of 0.92.

Looking at the components above, we can see that all the input variables are negatively weighted. This means that the more negative the value of a given datapoint, the higher the religiosity.

Analyzing the relationship between the variables of interest by performing propensity score matching

Starting off by trying to study the (rough) effect of the primary factor obtained from above.

In [164]:
```
# Credit to volodymyr, stackexchange contributor
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import NearestNeighbors

def get_matching_pairs(treated_df, non_treated_df, scaler=True):
    treated_x = treated_df.values
    non_treated_x = non_treated_df.values
    if (scaler==True):
        scaler=StandardScaler()
    if (scaler):
        scaler.fit(treated_x)
        treated_x=scaler.transform(treated_x)
        non_treated_x=scaler.transform(non_treated_x)
    nbrs=NearestNeighbors(n_neighbors=1,algorithm='ball_tree').fit(non_t
reated_x)
    distances,indices=nbrs.kneighbors(treated_x)
    indices=indices.reshape(indices.shape[0])
    matched = indices
    return matched
```

Let's first define 'treated' and 'untreated' groups. Since we are primarily focusing on the primary factor from the factor analysis, let's look at the summary statistics of this variable.

In [165]:
```
scipy.stats.describe(explanatory_var_transformed[:, 0])
```

Out[165]:
```
DescribeResult(nobs=964, minmax=(-1.5341857802485117, 2.04453941414954
2), mean=8.844930320665147e-17, variance=0.9292641506111441, skewness=
0.3845519752369101, kurtosis=-0.8761730358797837)
```

Looking at the factor loadings in the previous section, we can Let's define the treated observations as those datapoints with the primary more negative than a standard deviation below the mean, and the rest as untreated observations.

In [166]:
```
mean = scipy.stats.describe(explanatory_var_transformed[:, 0]).mean
variance = scipy.stats.describe(explanatory_var_transformed[:, 0]).varia
nce
stdev = variance ** (1/2)
cutoff = mean - stdev / 2
```

In [167]:
```
# subsetting the treated and the control group
treated = gss_sub[gss_sub.FIRSTVAR < cutoff]
untreated = gss_sub[gss_sub.FIRSTVAR >= cutoff]
```

In [168]:
```
treated_sub_ = treated[['GOD','SAVESOUL','RELPERSN','ATTEND','FUND','PRA
Y',\
               'POLVIEWS','SEX','EDUC','SPFUND','BIBLE',\
               'SAVESOUL_RECODED','RELPERSN_RECODED','FUND_RECODED',\
               'PRAY_RECODED','SPFUND_RECODED','BIBLE_RECODED', 'AGE']]
untreated_sub_ = untreated[['GOD','SAVESOUL','RELPERSN','ATTEND','FUND',
'PRAY',\
               'POLVIEWS','SEX','EDUC','SPFUND','BIBLE',\
               'SAVESOUL_RECODED','RELPERSN_RECODED','FUND_RECODED',\
               'PRAY_RECODED','SPFUND_RECODED','BIBLE_RECODED', 'AGE']]
```

In [169]:
```
treated_sub = treated[['POLVIEWS','SEX','EDUC', 'AGE']]
untreated_sub = untreated[['POLVIEWS','SEX','EDUC', 'AGE']]
```

In [170]:
```
matched_indices = get_matching_pairs(treated_sub, untreated_sub, scaler=
False)
```

In [171]:
```
# permissibility of homosexuality
```

In [184]:
```
s = 0
for i in range(matched_indices.shape[0]):
    t = treated.iloc[i].HOMOSEX_RECODED
    c = untreated.iloc[matched_indices, :].iloc[i].HOMOSEX_RECODED
    if (np.isfinite(t) & np.isfinite(c)):
        s += t - c
estimated_ATE = s / matched_indices.shape[0]
estimated_ATE
```

Out[184]: 0.4401114206128134

This estimate is probably still highly biased, because of other unmeasured confounding variables.

In [185]:
```
# permissibility of marriage w black person
```

In [186]:
```
s = 0
for i in range(matched_indices.shape[0]):
    if((treated.iloc[i].MARBLK != 0) & (untreated.iloc[i].MARBLK != 0)):
        t = treated.iloc[i].MARBLK
        c = untreated.iloc[matched_indices, :].iloc[i].MARBLK
        if (np.isfinite(t) & np.isfinite(c)):
            s += t - c
estimated_ATE = s / matched_indices.shape[0]
estimated_ATE
```

Out[186]: 0.31754874651810583

This estimate too is probably still highly biased, because of other unmeasured confounding variables.

Logistic Regression

In [181]:

```
X = gss_sub[gss_sub.MARBLK != 0][['FIRSTVAR', 'SECONDVAR', 'THIRDVAR',
'POLVIEWS','SEX','EDUC', 'AGE']]
Y = gss_sub[gss_sub.MARBLK != 0][['MARBLK']]

from sklearn.linear_model import LogisticRegression
clf = LogisticRegression().fit(X, Y.values.ravel())
clf.coef_
```

Out[181]:

```
array([[-0.2862295 ,  0.30377321, -0.2434898 , -0.11573444,  0.2472984
4,
        -0.01921031, -0.01833321],
       [-0.21084918, -0.16977175, -0.10936702, -0.05815125,  0.0024880
8,
        -0.09381839,  0.00600501],
       [ 0.37255638,  0.04244456,  0.07645245,  0.00474896,  0.1974878
8,
         0.06688131, -0.01715535],
       [-0.16107008, -0.14200686,  0.09286468,  0.07293203, -0.7863305
5,
        -0.06899753,  0.02422337],
       [-0.43404088, -0.25381865,  0.13227069, -0.02746535, -1.1994679
4,
        -0.15937236,  0.0404954 ]])
```

In [176]:

```
clf.coef_[:, 0]
```

Out[176]:

```
array([-0.02758279, -0.24469   , -0.2085951 ,  0.27020994, -0.179227  ,
       -0.47340233])
```

In [179]:
```
temp = gss_sub.copy()
temp = temp[temp.HOMOSEX_RECODED == temp.HOMOSEX_RECODED]

X = temp[['FIRSTVAR', 'SECONDVAR', 'THIRDVAR', 'POLVIEWS','SEX','EDUC',
'AGE']]
Y = temp[['HOMOSEX_RECODED']]

from sklearn.linear_model import LogisticRegression
clf = LogisticRegression().fit(X, Y.values.ravel())
clf.coef_
```

Out[179]:
```
array([[ 1.23908776e+00,  2.28987260e-01, -1.53539238e-01,
        -2.74372190e-01,  6.14339833e-01,  1.35909580e-01,
        -1.98136292e-02],
       [-7.22994384e-02,  1.50599727e-01, -3.27131149e-01,
        -1.24592041e-01, -5.34758398e-01, -4.33617211e-02,
        -4.69594564e-04],
       [-2.25946319e-01, -4.08828270e-01, -1.82003924e-01,
         1.43857521e-01, -1.77029462e-01, -1.64188441e-01,
         7.31669678e-03],
       [-1.33953461e+00, -2.09935347e-01,  1.86867703e-01,
         2.32561810e-01, -5.69205227e-01, -1.39581745e-01,
         1.21230762e-02]])
```

In [180]:
```
clf.coef_[:, 0]
```

Out[180]:
```
array([ 1.23908776, -0.07229944, -0.22594632, -1.33953461])
```

Rough

In [178]:
```
gss_sub['HOMOSEX_RECODED'].unique()
```

Out[178]:
```
array([ 1., nan,  4.,  3.,  2.])
```