Lab 1 - Time Series Trends

Your name

Harley & Firebaugh in 1993 wrote, "the most interesting thing about belief in an afterlife in the United States is what it is not doing: It is not declining." But that was a long time ago, so it is worth seeing if now, over the more recent two decades, belief in the afterlife has begun decline. They looked at age and cohort to understand the trends, but we will look at people who identify with a religion vs. saying they are part of no religion.

Here we will load in some packages and also load in the GSS data directly from the website. We will create two sets of variables. One set will use numeric value lables for the variables, while the other set will be categorical names for the labels (these will be prefaced with a z in front of each variable). This is a very complicated dataset to load in, so I create a bunch of code to do some things to it ... please don't worry about them for now. Just enjoy working with the dataset!

```
import pandas as pd
import requests
import zipfile
import io
from tqdm.notebook import tqdm
```

```
# Step 1: Download the ZIP file with progress bar
url = 'https://gss.norc.org/content/dam/gss/get-the-data/documents/stata/GSS_stata.zip'

# Make a streaming request to get the content in chunks
response = requests.get(url, stream=True)
total_size = int(response.headers.get('content-length', 0))  # Get the total file size
block_size = 1024  # 1 Kilobyte

# Progress bar for downloading
tqdm_bar = tqdm(total=total_size, unit='iB', unit_scale=True)
content = io.BytesIO()

# Download the file in chunks with progress bar
for data in response.iter_content(block_size):
    tqdm_bar.update(len(data))
    content.write(data)

tqdm_bar.close()

# Check if the download is successful
if total_size != 0 and tqdm_bar.n != total_size:
    print("Error in downloading the file.")
else:
    print("Download completed!")

# Step 2: Extract the ZIP file in memory and display progress
with zipfile.ZipFile(content) as z:
    # List all files in the zip
    file_list = z.namelist()

    # Filter for the .dta file (assuming there is only one)
    stata_files = [file for file in file_list if file.endswith('.dta')]

    # If there is a Stata file, proceed to extract and read it
    if stata_files:
        stata_file = stata_files[0]  # Take the first .dta file
        with z.open(stata_file) as stata_file_stream:
            # Step 3a: Load only the selected columns into a pandas DataFrame with numeric labels
            columns_to_load = ['id', 'degree', 'marital', 'sex', 'year', 'age', 'region', 'life', 'suicide1', 'marhomo']
            print("Loading selected columns from Stata file with numeric labels...")
            df_numeric = pd.read_stata(stata_file_stream, columns=columns_to_load, convert_categoricals=False)
            print("Data with numeric labels loaded successfully!")

        # Reload the dataset to get categorical (string) labels
        with z.open(stata_file) as stata_file_stream:
            print("Loading selected columns from Stata file with string (categorical) labels...")
            df_categorical = pd.read_stata(stata_file_stream, columns=columns_to_load)
            print("Data with categorical labels loaded successfully!")

```

```
            # Step 3b: Rename the categorical columns by prefixing with 'z' (no period)
            df_categorical = df_categorical.rename(columns={col: f'z{col}' for col in df_categorical.columns})

# Step 4: Concatenate the numeric and categorical DataFrames side by side
df = pd.concat([df_numeric, df_categorical], axis=1)

# Step 5: Display the first few rows of the final DataFrame
df.head()
```

```
100%                                   81.9M/81.9M [00:01<00:00, 67.1MiB/s]
Download completed!
Loading selected columns from Stata file with numeric labels...
Data with numeric labels loaded successfully!
Loading selected columns from Stata file with string (categorical) labels...
<ipython-input-20-cbdf6aa4c853>:47: UnicodeWarning:
One or more strings in the dta file could not be decoded using utf-8, and
so the fallback encoding of latin-1 is being used.  This can happen when a file
has been incorrectly encoded by Stata or some other software. You should verify
the string values returned are correct.
  df_categorical = pd.read_stata(stata_file_stream, columns=columns_to_load)
Data with categorical labels loaded successfully!
```

	id	degree	marital	sex	year	age	region	life	suicide1	marhomo	zid	zdegree	zmarital	zsex	zyear	zage	zregion	zlife	zsu
0	1	3.0	5.0	2.0	1972	23.0	3	NaN	NaN	NaN	1	bachelor's	never married	female	1972	23.0	east north central	NaN	
1	2	0.0	1.0	1.0	1972	70.0	3	NaN	NaN	NaN	2	less than high school	married	male	1972	70.0	east north central	NaN	

```
from __future__ import division
import numpy as np
import statsmodels.api as sm
import statsmodels.formula.api as smf
import os
import matplotlib.pyplot as plt
from scipy.stats import skew, kurtosis
import seaborn as sns
```

1. Conduct a trend analysis of some variable of interest. Graph it and try different functional forms. Look for subgroup variation across time, too. Extra credit if you consider other variables as a means of explaining the trend. Explain all of your results.

I will begin by examining what the overall trend in belief in the afterlife has been for the last 50 years.

NOTE: I subset my dataset to only include observations that are not missing on any of the following: 'year', 'relig', postlife' -- that is what the dataframe "df_clean" is.

```
# Step 1: Drop observations with NA values in any variable listed
df_clean = df.dropna(subset=['year', 'life', 'suicide1', 'marhomo'])
df_clean.head()

```

	id	degree	marital	sex	year	age	region	life	suicide1	marhomo	zid	zdegree	zmarital	zsex	zyear	zage	zregion	zlif
21879	5	3.0	5.0	1.0	1988	25.0	2	1.0	1.0	4.0	5	bachelor's	never married	male	1988	25.0	middle atlantic	excitin
21882	8	1.0	3.0	2.0	1988	27.0	2	2.0	1.0	2.0	8	high school	divorced	female	1988	27.0	middle atlantic	routin
21884	10	0.0	5.0	1.0	1988	50.0	2	2.0	2.0	4.0	10	less than high school	never married	male	1988	50.0	middle atlantic	routin

```
plt.figure(figsize=(10, 6))
sns.lineplot(x='year', y='marhomo', data=mean_marhomo_per_year)
plt.title('Proportion of People Who Say "Yes, Same-Sex Marriage" Per Year (Binary Variable)')
plt.xlabel('Year')
plt.ylabel('Proportion (Mean)')
plt.grid(True)
plt.show()

```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-27-f4edeeca47eb> in <cell line: 2>()
      1 plt.figure(figsize=(10, 6))
----> 2 sns.lineplot(x='year', y='marhomo', data=mean_marhomo_per_year)
      3 plt.title('Proportion of People Who Say "Yes, Same-Sex Marriage" Per Year (Binary Variable)')
      4 plt.xlabel('Year')
      5 plt.ylabel('Proportion (Mean)')

5 frames
/usr/local/lib/python3.10/dist-packages/seaborn/_core/data.py in _assign_variables(self, data, variables)
    230                 else:
    231                     err += "An entry with this name does not appear in `data`."
--> 232                 raise ValueError(err)
    233
    234             else:

ValueError: Could not interpret value `marhomo` for `y`. An entry with this name does not appear in `data`.
```

This appears to show something of an upward trajectory on this trend over time, meaning more people are believing in the afterlife now than 50 years ago. This is not what would be theorized, based on the previous studies!

```
1 df_clean.groupby('year')['natarms'].apply(lambda x: (x == 'yes').mean() * 100).reset_index()
```

	year	zpostlife
0	1973	76.979472
1	1975	74.533234
2	1976	78.248175
3	1978	76.740847
4	1980	81.245254
5	1983	73.623385
6	1984	79.451039
7	1986	81.938326
8	1987	77.904192
9	1988	79.416058
10	1989	75.964719
11	1990	78.414634
12	1991	80.528053
13	1993	80.893043
14	1994	81.314286
15	1996	82.305476
16	1998	81.657675
17	2000	81.725642
18	2002	80.414938
19	2004	81.934932
20	2006	82.786260
21	2008	81.460674
22	2010	81.079577
23	2012	80.817253
24	2014	79.569892
25	2016	80.714009
26	2018	80.986249
27	2022	81.165049

```
# Step 1: Run the regression using the formula interface
model0 = smf.ols(formula='zpostlife_binary ~ year', data=df_clean)

# Step 2: Fit the model
results0 = model0.fit()

# Step 3: Output the summary of the regression
print(results0.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       zpostlife_binary   R-squared:                       0.001
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     48.69
Date:                Thu, 19 Sep 2024   Prob (F-statistic):           3.04e-12
Time:                        18:47:16   Log-Likelihood:                -22049.
No. Observations:               43985   AIC:                         4.410e+04
Df Residuals:                   43983   BIC:                         4.412e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     -1.0848      0.270     -4.015      0.000      -1.614      -0.555
year           0.0009      0.000      6.978      0.000       0.001       0.001
==============================================================================
Omnibus:                     9260.423   Durbin-Watson:                   1.932
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            16639.050
Skew:                          -1.501   Prob(JB):                         0.00
Kurtosis:                       3.260   Cond. No.                     2.83e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.83e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

If we simply include a linear time trend, we see that it is quite statistically signifacant, such that for each year that goes by, the percentage of people who say they believe in the afterlife goes up by 0.09 percentage points per year. This is quite statistically significant, though the R-sq is quite small, with time explaining only 0.1% of all variation in belief in the afterlife.

```
# Step 1: Run the regression using the formula interface
model = smf.ols(formula='zpostlife_binary ~ C(year)', data=df_clean)

# Step 2: Fit the model
results = model.fit()

# Step 3: Output the summary of the regression
print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       zpostlife_binary   R-squared:                       0.003
Model:                            OLS   Adj. R-squared:                  0.003
Method:                 Least Squares   F-statistic:                     5.260
Date:                Thu, 19 Sep 2024   Prob (F-statistic):           1.54e-17
Time:                        18:47:19   Log-Likelihood:                -22002.
No. Observations:               43985   AIC:                         4.406e+04
Df Residuals:                   43957   BIC:                         4.430e+04
Df Model:                          27
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Intercept             0.7698      0.011     71.226      0.000       0.749       0.791
C(year)[T.1975]      -0.0245      0.015     -1.593      0.111      -0.055       0.006
C(year)[T.1976]       0.0127      0.015      0.831      0.406      -0.017       0.043
C(year)[T.1978]      -0.0024      0.015     -0.157      0.875      -0.032       0.027
C(year)[T.1980]       0.0427      0.015      2.766      0.006       0.012       0.073
C(year)[T.1983]      -0.0336      0.015     -2.237      0.025      -0.063      -0.004
C(year)[T.1984]       0.0247      0.015      1.612      0.107      -0.005       0.055
C(year)[T.1986]       0.0496      0.015      3.243      0.001       0.020       0.080
C(year)[T.1987]       0.0092      0.015      0.635      0.526      -0.019       0.038
C(year)[T.1988]       0.0244      0.015      1.596      0.111      -0.006       0.054
C(year)[T.1989]      -0.0101      0.017     -0.593      0.553      -0.044       0.023
C(year)[T.1990]       0.0144      0.018      0.814      0.416      -0.020       0.049
C(year)[T.1991]       0.0355      0.017      2.076      0.038       0.002       0.069
C(year)[T.1993]       0.0391      0.017      2.329      0.020       0.006       0.072
C(year)[T.1994]       0.0433      0.014      3.007      0.003       0.015       0.072
C(year)[T.1996]       0.0533      0.014      3.687      0.000       0.025       0.082
```

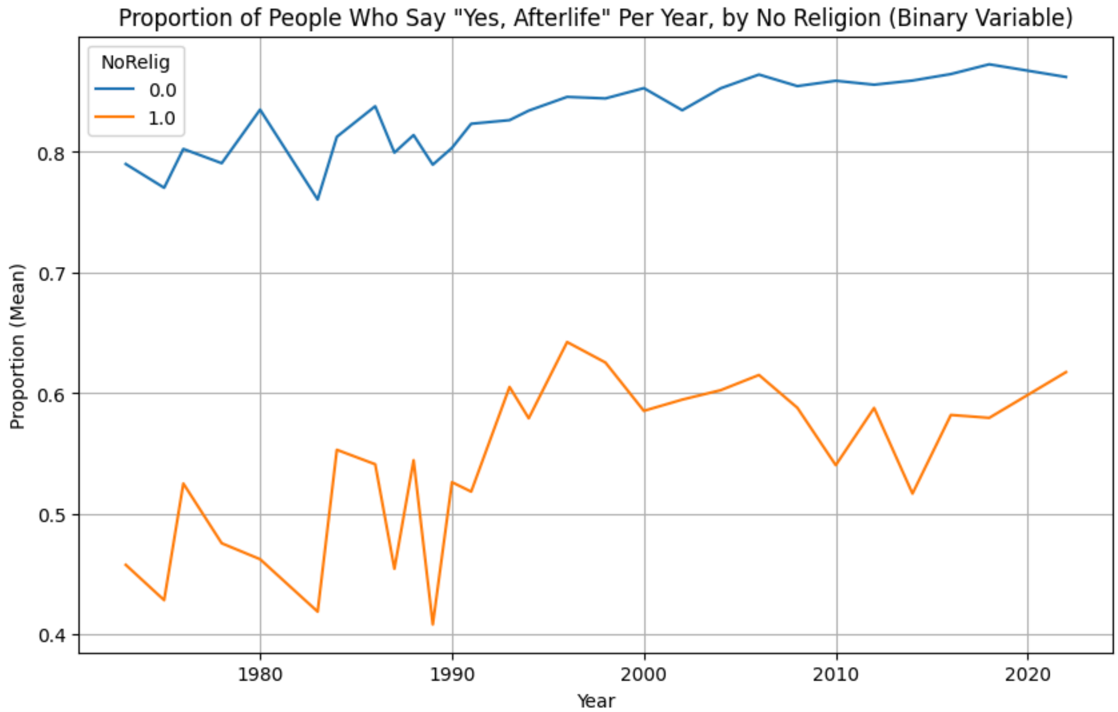
```
C(year)[T.1998]     0.0468      0.014      3.351      0.001       0.019       0.074
C(year)[T.2000]     0.0475      0.014      3.407      0.001       0.020       0.075
C(year)[T.2002]     0.0344      0.016      2.177      0.029       0.003       0.065
C(year)[T.2004]     0.0496      0.016      3.114      0.002       0.018       0.081
C(year)[T.2006]     0.0581      0.013      4.357      0.000       0.032       0.084
C(year)[T.2008]     0.0448      0.014      3.120      0.002       0.017       0.073
C(year)[T.2010]     0.0410      0.014      2.860      0.004       0.013       0.069
C(year)[T.2012]     0.0384      0.014      2.666      0.008       0.010       0.067
C(year)[T.2014]     0.0259      0.014      1.888      0.059      -0.001       0.053
C(year)[T.2016]     0.0373      0.013      2.794      0.005       0.011       0.064
C(year)[T.2018]     0.0401      0.014      2.889      0.004       0.013       0.067
C(year)[T.2022]     0.0419      0.015      2.822      0.005       0.013       0.071
==============================================================================
Omnibus:                     9226.357   Durbin-Watson:                   1.936
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            16542.923
Skew:                          -1.497   Prob(JB):                         0.00
Kurtosis:                       3.260   Cond. No.                         31.1
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

If we include year dummies in the model instead, we see that most of the years, especially after 1993, are statistically different from the first year of data in 1973. In fact, in 2022, 4.2 percentage points more people said they believed in the afterlife, compared to in 1973 -- and this difference appears statistically significant. For what it is worth, the Rsq tripled to 0.3% being explainable by year dummies.

I then turned to look for subgroup variation across time, too. I looked at whether there are differences in the trends for people who identify with a religion vs. saying they are part of no religion. I would think that those who do not identify with a religion might not share a belief in the afterlife.

```python
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

# Step 1: Define conditions and choices for the  variable
relig_conditions = [
    (df_clean['relig'] == 4),  # 4 is "no religion"
    (df_clean['relig'] != 4)    # everything else is a religion
]

relig_choices = [1, 0]  # 1 if relig==4, otherwise 0

# Step 2: Use np.select to create a new binary variable based on the conditions
df_clean['norelig_binary'] = np.select(relig_conditions, relig_choices, default=np.nan)

# Step 3: Calculate the mean of the new binary variable by year and relig group
mean_postlife_per_year_norelig = df_clean.groupby(['year', 'norelig_binary'])['zpostlife_binary'].mean().reset_index()

# Step47: Plot the mean of the binary  variable by year, split by relig
plt.figure(figsize=(10, 6))
sns.lineplot(x='year', y='zpostlife_binary', hue='norelig_binary', data=mean_postlife_per_year_norelig)
plt.title('Proportion of People Who Say "Yes, Afterlife" Per Year, by No Religion (Binary Variable)')
plt.xlabel('Year')
plt.ylabel('Proportion (Mean)')
plt.legend(title='NoRelig')  # Automatically create the legend based on hue
plt.grid(True)
plt.show()


```

```
<ipython-input-35-1807c416f723>:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-cc
  df_clean['norelig_binary'] = np.select(relig_conditions, relig_choices, default=np.nan)
```



Not surprisingly, those with no religion are much less likely to believe in the afterlife (usually approximately 30 percentage points lower than those who do say they have a religion), but the trends look pretty similar. Those without religion have increased their belief in the afterlife too! And by a margin similar to those with a religion, or at least that is what it looks like from the graph.

```
1 model2 = smf.ols(formula='zpostlife_binary ~ year + norelig_binary', data=df_clean)
2
3 # Step 1: Fit the model
4 results2 = model2.fit()
5
6 # Step 2: Output the summary of the regression
7 print(results2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       zpostlife_binary   R-squared:                       0.052
Model:                            OLS   Adj. R-squared:                  0.052
Method:                 Least Squares   F-statistic:                     1216.
Date:                Thu, 19 Sep 2024   Prob (F-statistic):               0.00
Time:                        18:47:27   Log-Likelihood:                -20889.
No. Observations:               43985   AIC:                         4.178e+04
Df Residuals:                   43982   BIC:                         4.181e+04
Df Model:                           2
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
Intercept         -3.0174      0.266    -11.339      0.000      -3.539      -2.496
year               0.0019      0.000     14.469      0.000       0.002       0.002
norelig_binary    -0.2807      0.006    -48.800      0.000      -0.292      -0.269
==============================================================================
Omnibus:                     8795.731   Durbin-Watson:                   1.940
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            15232.871
Skew:                          -1.427   Prob(JB):                         0.00
Kurtosis:                       3.411   Cond. No.                     2.87e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.87e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

We see that on average, a person without religion is expected to say they believe in an afterlife by .28 percentage points, net of year. That upped the Rsq considerable, to 5.2% variation explained now.

```
model3 = smf.ols(formula='zpostlife_binary ~ year*norelig_binary', data=df_clean)

# Step 1: Fit the model
results3 = model3.fit()

# Step 2: Output the summary of the regression
print(results3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:       zpostlife_binary   R-squared:                       0.052
Model:                            OLS   Adj. R-squared:                  0.052
Method:                 Least Squares   F-statistic:                     811.1
Date:                Thu, 19 Sep 2024   Prob (F-statistic):               0.00
Time:                        18:47:30   Log-Likelihood:                -20889.
No. Observations:               43985   AIC:                         4.179e+04
Df Residuals:                   43981   BIC:                         4.182e+04
Df Model:                           3
Covariance Type:            nonrobust
=======================================================================================
                          coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------
Intercept              -2.9416      0.282    -10.419      0.000      -3.495      -2.388
year                    0.0019      0.000     13.369      0.000       0.002       0.002
norelig_binary         -0.9625      0.848     -1.136      0.256      -2.624       0.699
year:norelig_binary     0.0003      0.000      0.804      0.421      -0.000       0.001
==============================================================================
Omnibus:                     8800.189   Durbin-Watson:                   1.940
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            15243.429
Skew:                          -1.427   Prob(JB):                         0.00
Kurtosis:                       3.413   Cond. No.                     9.27e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.27e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

When we interact year with "no religion" we see that the interaction is not statistically significant (P>|t| of .428), suggesting that the two groups are increasing their belief in the afterlife at the same rate.

So our big conclusion is that no one really would have predicted this! Harley & Firebaugh has expected that that belief in an afterlife in the United States would have been declining, but they found that belief was flat. Now, 30 years later, we see that it is not even just flat anymore ... it is actually increasing, and not just for those who have a religion, but for those without a religion too. Fascinating!