ds102_project_code

December 11, 2022

1 Data 102: Final Project Code

1.1 American Partisanship in Relation to National Attention and Citizen Engagement

First, we load in all the necessary Python packages for analysis.

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats.stats import pearsonr
import statsmodels.api as sm
!pip install causalinference
from causalinference import CausalModel
```

```
Collecting causalinference
  Using cached CausalInference-0.1.3-py3-none-any.whl (51 kB)
Installing collected packages: causalinference
Successfully installed causalinference-0.1.3
```

1.2 Data Cleaning

We begin by loading in the first table from the US census data (population and voter turnout data), cleaning up the strings and converting relevant columns to integers.

[2]:
```
voting = pd.read_csv('table01.csv')
voting.columns = voting.iloc[1]
voting = voting.iloc[3:439, :]
voting.columns.values[1] = 'state_ab'
voting.columns.values[2] = 'state_name'
voting.columns.values[3] = 'district'
voting.columns.values[4] = 'num_votes_cast'
voting['num_votes_cast'] = pd.to_numeric(voting['num_votes_cast'].str.
 ↪replace(',', '').str.replace('-', '0'))
voting.columns.values[5] = 'voting_pop'
voting['voting_pop'] = pd.to_numeric(voting['voting_pop'].str.replace(',', ''))
voting.columns.values[7] = 'voting_percent'
```

```
voting['voting_percent'] = pd.to_numeric(voting['voting_percent'].str.
 ↪replace('-', '0'))/100
voting = voting[['state_ab', 'state_name', 'district', 'num_votes_cast',␣
 ↪'voting_pop', 'voting_percent']]
voting = voting.reset_index().drop(columns='index')
voting.columns.name = None
voting.head()
```

[2]:

	state_ab	state_name	district	num_votes_cast	voting_pop	voting_percent
0	AL	Alabama	1	242617	544464	0.446
1	AL	Alabama	2	226230	516295	0.438
2	AL	Alabama	3	231915	543854	0.426
3	AL	Alabama	4	230969	515701	0.448
4	AL	Alabama	5	260673	551968	0.472

We then load in the next census table (age distributions of districts) and clean it up as well.

[3]:
```
age = pd.read_csv('table02a.csv')
age.columns = age.iloc[1]
age = age.iloc[4:440, [1, 2, 3, 6, 8, 10, 12, 14, 16, 18, 20]]
age.columns.values[0] = 'state_ab'
age.columns.values[1] = 'state_name'
age.columns.values[2] = 'district'
age.columns.values[3] = '18-29_pop'
age.columns.values[4] = '18-29_percent'
age.columns.values[5] = '30-44_pop'
age.columns.values[6] = '30-44_percent'
age.columns.values[7] = '45-64_pop'
age.columns.values[8] = '45-64_percent'
age.columns.values[9] = '65_plus_pop'
age.columns.values[10] = '65_plus_percent'
for col in ['18-29_pop', '30-44_pop', '45-64_pop', '65_plus_pop']:
    age[col] = pd.to_numeric(age[col].str.replace(',', ''))
for col in ['18-29_percent', '30-44_percent', '45-64_percent',␣
 ↪'65_plus_percent']:
    age[col] = pd.to_numeric(age[col])/100
age = age.reset_index().drop(columns='index')
age.columns.name = None
age.head()
```

[3]:

	state_ab	state_name	district	18-29_pop	18-29_percent	30-44_pop	\
0	AL	Alabama	1	104060	0.191	125900	
1	AL	Alabama	2	109222	0.212	118999	
2	AL	Alabama	3	121328	0.223	121212	
3	AL	Alabama	4	95990	0.186	114921	
4	AL	Alabama	5	109986	0.199	129788	

```
   30-44_percent  45-64_pop  45-64_percent  65_plus_pop  65_plus_percent
0          0.231     188031          0.345       126473            0.232
1          0.230     173351          0.336       114723            0.222
2          0.223     182379          0.335       118935            0.219
3          0.223     177247          0.344       127543            0.247
4          0.235     193348          0.350       118846            0.215
```

Next we load in the census table on sex and poverty and clean it up.

[4]:
```
sex_poverty = pd.read_csv('table02b.csv')
sex_poverty.columns = sex_poverty.iloc[1]
sex_poverty = sex_poverty.iloc[4:440, [1, 2, 3, 6, 8, 10, 12, 16, 18]]
sex_poverty.columns.values[0] = 'state_ab'
sex_poverty.columns.values[1] = 'state_name'
sex_poverty.columns.values[2] = 'district'
sex_poverty.columns.values[3] = 'men_pop'
sex_poverty.columns.values[4] = 'men_percent'
sex_poverty.columns.values[5] = 'women_pop'
sex_poverty.columns.values[6] = 'women_percent'
sex_poverty.columns.values[7] = 'poverty_pop'
sex_poverty.columns.values[8] = 'poverty_percent'
for col in ['men_pop', 'women_pop', 'poverty_pop']:
    sex_poverty[col] = pd.to_numeric(sex_poverty[col].str.replace(',', ''))
for col in ['men_percent', 'women_percent', 'poverty_percent']:
    sex_poverty[col] = pd.to_numeric(sex_poverty[col])/100
sex_poverty = sex_poverty.reset_index().drop(columns='index')
sex_poverty.columns.name = None
sex_poverty.head()
```

[4]:
```
  state_ab state_name district  men_pop  men_percent  women_pop  \
0       AL    Alabama        1   256603        0.471     287861
1       AL    Alabama        2   243971        0.473     272324
2       AL    Alabama        3   261066        0.480     282788
3       AL    Alabama        4   248166        0.481     267535
4       AL    Alabama        5   267633        0.485     284335

   women_percent  poverty_pop  poverty_percent
0          0.529        76483            0.144
1          0.527        75815            0.152
2          0.520        88748            0.169
3          0.519        70775            0.139
4          0.515        61196            0.114
```

The next table is about education distributions in each US district.

[5]:
```
education = pd.read_csv('table02c.csv')
education.columns = education.iloc[1]
```

```
education = education.iloc[4:440, [1, 2, 3, 6, 8, 10, 12, 14, 16, 18, 20, 22,␣
 ↪24, 26, 28, 30, 32]]
education.columns.values[0] = 'state_ab'
education.columns.values[1] = 'state_name'
education.columns.values[2] = 'district'
education.columns.values[3] = 'less_9th_pop'
education.columns.values[4] = 'less_9th_percent'
education.columns.values[5] = '9th-12th_pop'
education.columns.values[6] = '9th-12th_percent'
education.columns.values[7] = 'high_school_pop'
education.columns.values[8] = 'high_school_percent'
education.columns.values[9] = 'some_college_pop'
education.columns.values[10] = 'some_college_percent'
education.columns.values[11] = 'associates_pop'
education.columns.values[12] = 'associates_percent'
education.columns.values[13] = 'bachelors_pop'
education.columns.values[14] = 'bachelors_percent'
education.columns.values[15] = 'graduate_pop'
education.columns.values[16] = 'graduate_percent'
for col in ['less_9th_pop', '9th-12th_pop', 'high_school_pop',␣
 ↪'some_college_pop', 'associates_pop', 'bachelors_pop', 'graduate_pop']:
    education[col] = pd.to_numeric(education[col].str.replace(',', ''))
for col in ['less_9th_percent', '9th-12th_percent', 'high_school_percent',␣
 ↪'some_college_percent', 'associates_percent', 'bachelors_percent',␣
 ↪'graduate_percent']:
    education[col] = pd.to_numeric(education[col])/100
education = education.reset_index().drop(columns='index')
education.columns.name = None
education.head()
```

[5]:

	state_ab	state_name	district	less_9th_pop	less_9th_percent	9th-12th_pop
0	AL	Alabama	1	13409	0.025	57234
1	AL	Alabama	2	18295	0.035	53192
2	AL	Alabama	3	19578	0.036	56833
3	AL	Alabama	4	24346	0.047	57850
4	AL	Alabama	5	14908	0.027	43805

	9th-12th_percent	high_school_pop	high_school_percent	some_college_pop
0	0.105	185503	0.341	122236
1	0.103	172427	0.334	119350
2	0.105	174209	0.320	142705
3	0.112	175806	0.341	121739
4	0.079	151609	0.275	123272

	some_college_percent	associates_pop	associates_percent	bachelors_pop
0	0.225	42603	0.078	82971
1	0.231	45677	0.088	69082

```
2                 0.262           45713               0.084          63916
3                 0.236           51436               0.100          52697
4                 0.223           45097               0.082         113417

   bachelors_percent  graduate_pop  graduate_percent
0              0.152         40508             0.074
1              0.134         38272             0.074
2              0.118         40900             0.075
3              0.102         31827             0.062
4              0.205         59860             0.108
```

Lastly, we load in data on race distributions and clean it up.

[6]:
```
race = pd.read_csv('table02d.csv')
race.columns = race.iloc[1]
race = race.iloc[4:440, [1, 2, 3, 6, 8, 10, 12, 14, 16, 18, 20, 22, 24, 26, 28,␣
 ↪30, 32, 34, 36]]
race.columns.values[0] = 'state_ab'
race.columns.values[1] = 'state_name'
race.columns.values[2] = 'district'
race.columns.values[3] = 'white_pop'
race.columns.values[4] = 'white_percent'
race.columns.values[5] = 'black_pop'
race.columns.values[6] = 'black_percent'
race.columns.values[7] = 'asian_pop'
race.columns.values[8] = 'asian_percent'
race.columns.values[9] = 'amer_indian_pop'
race.columns.values[10] = 'amer_indian_percent'
race.columns.values[11] = 'nat_hawaiian_pop'
race.columns.values[12] = 'nat_hawaiian_percent'
race.columns.values[13] = 'other_race_pop'
race.columns.values[14] = 'other_race_percent'
race.columns.values[15] = 'two_more_race_pop'
race.columns.values[16] = 'two_more_race_percent'
race.columns.values[17] = 'hispanic_pop'
race.columns.values[18] = 'hispanic_percent'
for col in ['white_pop', 'black_pop', 'asian_pop', 'amer_indian_pop',␣
 ↪'nat_hawaiian_pop', 'other_race_pop', 'two_more_race_pop', 'hispanic_pop']:
    race[col] = pd.to_numeric(race[col].str.replace('N', '0').str.replace(',',␣
 ↪''))
for col in ['white_percent', 'black_percent', 'asian_percent',␣
 ↪'amer_indian_percent', 'nat_hawaiian_percent', 'other_race_percent',␣
 ↪'two_more_race_percent', 'hispanic_percent']:
    race[col] = pd.to_numeric(race[col].str.replace('N', '0'))/100
race = race.reset_index().drop(columns='index')
race.columns.name = None
race.head()
```

[6]:

	state_ab	state_name	district	white_pop	white_percent	black_pop	black_percent	asian_pop	asian_percent	amer_indian_pop	amer_indian_percent	nat_hawaiian_pop	nat_hawaiian_percent	other_race_pop	other_race_percent	two_more_race_pop	two_more_race_percent	hispanic_pop	hispanic_percent
0	AL	Alabama	1	379018	0.696	144187	0.265	6506	0.012	0	0.0	0	0.0	2884	0.005	7325	0.013	11678	0.021
1	AL	Alabama	2	338162	0.655	162707	0.315	3817	0.007	0	0.0	0	0.0	1818	0.004	7705	0.015	9755	0.019
2	AL	Alabama	3	390539	0.718	139026	0.256	4028	0.007	0	0.0	0	0.0	2448	0.005	6754	0.012	12241	0.023
3	AL	Alabama	4	459105	0.890	39714	0.077	0	0.000	0	0.0	0	0.0	3529	0.007	8327	0.016	11700	0.023
4	AL	Alabama	5	427462	0.774	99160	0.180	5209	0.009	0	0.0	0	0.0	5852	0.011	12317	0.022	14670	0.027

Finally, we merge together all the census data to get population data on all 435 US congressional districts.

[7]:
```
census_data = pd.merge(left = voting, right = age, how = 'inner', on =␣
 ↪['state_ab', 'state_name', 'district'])
census_data = pd.merge(left = census_data, right = sex_poverty, how = 'inner',␣
 ↪on = ['state_ab', 'state_name', 'district'])
census_data = pd.merge(left = census_data, right = education, how = 'inner', on␣
 ↪= ['state_ab', 'state_name', 'district'])
census_data = pd.merge(left = census_data, right = race, how = 'inner', on =␣
 ↪['state_ab', 'state_name', 'district'])
census_data.head()
```

[7]:
```
  state_ab state_name district  num_votes_cast  voting_pop  voting_percent  \
0       AL    Alabama        1          242617      544464           0.446
1       AL    Alabama        2          226230      516295           0.438
2       AL    Alabama        3          231915      543854           0.426
3       AL    Alabama        4          230969      515701           0.448
4       AL    Alabama        5          260673      551968           0.472

   18-29_pop  18-29_percent  30-44_pop  30-44_percent  …  amer_indian_pop  \
0     104060          0.191     125900          0.231  …                0
1     109222          0.212     118999          0.230  …                0
2     121328          0.223     121212          0.223  …                0
3      95990          0.186     114921          0.223  …                0
4     109986          0.199     129788          0.235  …                0

   amer_indian_percent  nat_hawaiian_pop  nat_hawaiian_percent  \
0                  0.0                 0                   0.0
1                  0.0                 0                   0.0
2                  0.0                 0                   0.0
3                  0.0                 0                   0.0
4                  0.0                 0                   0.0

   other_race_pop  other_race_percent  two_more_race_pop  \
0            2884               0.005               7325
1            1818               0.004               7705
2            2448               0.005               6754
3            3529               0.007               8327
4            5852               0.011              12317

   two_more_race_percent  hispanic_pop  hispanic_percent
0                  0.013         11678             0.021
1                  0.015          9755             0.019
2                  0.012         12241             0.023
3                  0.016         11700             0.023
4                  0.022         14670             0.027

[5 rows x 50 columns]
```

Now, we start looking at the FiveThirtyEight data on endorsements. We load in the table on Democratic primary candidates and keep the relevant endorsement columns. Then we group by district to have a row for each district.

[8]:
```
dem_candidates = pd.read_csv('dem_candidates.csv')
dem_candidates = dem_candidates[dem_candidates['Office Type'] ==␣
 ↪'Representative']
dem_candidates = dem_candidates.drop(dem_candidates.columns[[0, 3, 4, 5, 6, 7,␣
 ↪8, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19]], axis = 1)
```

```
dem_districts = dem_candidates.groupby(by = ['State', 'District', 'Partisan␣
 ↪Lean']).agg(np.any).reset_index()
dem_districts['District'] = dem_districts['District'].str.replace('[^0-9]', '',␣
 ↪regex=True)
dem_districts.head()
```

[8]:

	State	District	Partisan Lean	Emily Endorsed?	Guns Sense Candidate?	Biden Endorsed?	Warren Endorsed?	Sanders Endorsed?	Our Revolution Endorsed?	Justice Dems Endorsed?	PCCC Endorsed?	Indivisible Endorsed?	WFP Endorsed?	VoteVets Endorsed?	No Labels Support?
0	AL	1	-30.680000	False	False	False	False	False	False	False	False	False	False	False	False
1	AL	2	-33.080002	False	False	False	False	False	False	False	False	False	False	False	False
2	AL	3	-33.660000	False	True	False	False	False	False	False	False	False	False	False	False
3	AL	4	-62.480000	False	True	False	False	False	False	False	False	False	False	False	False
4	AL	5	-34.830002	False	False	False	False	False	False	False	False	True	False	False	False

Next, we load in the table on Republican primary candidates, clean it up, and group by district.

[9]:
```
rep_candidates = pd.read_csv('rep_candidates.csv', encoding = 'latin-1')
rep_candidates = rep_candidates[rep_candidates['Office Type'] ==␣
 ↪'Representative']
```

```
rep_candidates = rep_candidates.drop(rep_candidates.columns[[0, 3, 4, 5, 6, 7,␣
 ↪8, 9, 10, 11]], axis = 1)
rep_districts = rep_candidates.groupby(by = ['State', 'District']).agg(np.any).
 ↪reset_index()
rep_districts['District'] = rep_districts['District'].str.replace('[^0-9]', '',␣
 ↪regex=True)
rep_districts.head()
```

[9]:

	State	District	Trump Endorsed?	Bannon Endorsed?	Great America Endorsed?	NRA Endorsed?	Right to Life Endorsed?	Susan B. Anthony Endorsed?	Club for Growth Endorsed?	Koch Support?	House Freedom Support?	Tea Party Endorsed?	Main Street Endorsed?	Chamber Endorsed?	No Labels Support?
0	AZ	1	False	False	False	False	False	False	True	False	False	True	False	False	False
1	AZ	2	False	False	False	False	False	False	False	True	False	False	False	False	False
2	AZ	3	False	False	False	False	False	False	False	False	False	False	False	False	False
3	AZ	8	False	False	False	False	False	True	False	True	True	False	False	False	False
4	AZ	9	False	False	False	False	False	False	False	False	False	False	False	False	False

Now we perform an outer merge on the districts with Democratic primaries and districts with Republican primaries to include as many districts as possible.

[10]:
```
district_data = pd.merge(left = dem_districts, right = rep_districts, on =␣
↪['State', 'District'], how = 'outer')
district_data.head()
```

[10]:

	State	District	Partisan Lean	Emily Endorsed?	Guns Sense Candidate?	Biden Endorsed?	Warren Endorsed?	Sanders Endorsed?	Our Revolution Endorsed?	Justice Dems Endorsed?	…	NRA Endorsed?	Right to Life Endorsed?	Susan B. Anthony Endorsed?	Club for Growth Endorsed?	Koch Support?	House Freedom Support?	Tea Party Endorsed?	Main Street Endorsed?	Chamber Endorsed?	No Labels Support?_y
0	AL	1	-30.680000	False	False	False	False	False	False	False	…	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1	AL	2	-33.080002	False	False	False	False	False	False	False	…	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
2	AL	3	-33.660000	False	True	False	False	False	False	False	…	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
3	AL	4	-62.480000	False	True	False	False	False	False	False	…	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
4	AL	5	-34.830002	False	False	False	False	False	False	False	…	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	

```
0                   NaN
1                   NaN
2                   NaN
3                   NaN
4                   NaN

[5 rows x 28 columns]
```

Next, we make the groupings of endorsements as outlined in the report. We set a cell to True if any candidate in that district received an endorsement from an organization/person within that group.

[11]:
```
district_data['any_endorse'] = district_data.iloc[:, 3:].sum(1) > 0
district_data['gun_org_endorse'] = district_data[['NRA Endorsed?', 'Guns Sense␣
 ↪Candidate?']].sum(1) > 0
district_data['abortion_org_endorse'] = district_data[['Susan B. Anthony␣
 ↪Endorsed?', 'Right to Life Endorsed?', 'Emily Endorsed?']].sum(1) > 0
district_data['left_figure_endorse'] = district_data[['Biden Endorsed?',␣
 ↪'Warren Endorsed? ', 'Sanders Endorsed?']].sum(1) > 0
district_data['right_figure_endorse'] = district_data[['Trump Endorsed?',␣
 ↪'Bannon Endorsed?']].sum(1) > 0
district_data['political_figure_endorse'] =␣
 ↪district_data['left_figure_endorse'] + district_data['right_figure_endorse']
district_data['prog_org_endorse'] = district_data[['Our Revolution Endorsed?',␣
 ↪'Justice Dems Endorsed?', 'PCCC Endorsed?', 'Indivisible Endorsed?', 'WFP␣
 ↪Endorsed?']].sum(1) > 0
district_data['cons_org_endorse'] = district_data[['Great America Endorsed?',␣
 ↪'Club for Growth Endorsed?', 'Koch Support?', 'House Freedom Support?', 'Tea␣
 ↪Party Endorsed?', 'Main Street Endorsed?']].sum(1) > 0
district_endorsements = district_data[['State', 'District', 'Partisan Lean',␣
 ↪'any_endorse', 'gun_org_endorse', 'abortion_org_endorse',␣
 ↪'left_figure_endorse', 'right_figure_endorse', 'political_figure_endorse',␣
 ↪'prog_org_endorse', 'cons_org_endorse']]
district_endorsements = district_endorsements.rename(columns = {'State' :␣
 ↪'state_ab', 'District': 'district', 'Partisan Lean' : 'partisan_lean'})
district_endorsements['district'] = district_endorsements['district'].
 ↪replace('', '1')
district_endorsements.head()
```

[11]:
```
  state_ab district  partisan_lean  any_endorse  gun_org_endorse  \
0       AL        1     -30.680000        False            False
1       AL        2     -33.080002        False            False
2       AL        3     -33.660000         True             True
3       AL        4     -62.480000         True             True
4       AL        5     -34.830002         True            False

   abortion_org_endorse  left_figure_endorse  right_figure_endorse  \
0                 False                False                 False
```

```
1                False                False                False
2                False                False                False
3                False                False                False
4                False                False                False

   political_figure_endorse  prog_org_endorse  cons_org_endorse
0                     False             False             False
1                     False             False             False
2                     False             False             False
3                     False             False             False
4                     False              True             False
```

Now we load in the FiveThirtyEight data on partisan lean for all districts and clean it up.

[12]:
```
partisan_raw = pd.read_csv('fivethirtyeight_partisan_lean_DISTRICTS.csv')
partisan_data = pd.DataFrame(partisan_raw['district'].str.split('-').to_list(),␣
 ↪columns=['state_ab', 'district'])
partisan_data['abs_partisan_lean'] = partisan_raw['2018'].str.replace('[^.
 ↪0-9]', '', regex=True).astype(float)
partisan_data.head()
```

[12]:
```
  state_ab district  abs_partisan_lean
0       AK        1              15.21
1       AL        1              28.61
2       AL        2              30.97
3       AL        3              31.37
4       AL        4              59.81
```

We then merge the absolute partisan lean column into the district-level endorsements dataset.

[13]:
```
district_partisan = pd.merge(left = district_endorsements, right =␣
 ↪partisan_data, on = ['state_ab', 'district'], how = 'inner')
district_partisan = district_partisan.drop(columns = 'partisan_lean')
abs_partisan_lean = district_partisan.pop('abs_partisan_lean')
district_partisan.insert(2, 'abs_partisan_lean', abs_partisan_lean)
district_partisan.head()
```

[13]:
```
  state_ab district  abs_partisan_lean  any_endorse  gun_org_endorse  \
0       AL        1              28.61        False            False
1       AL        2              30.97        False            False
2       AL        3              31.37         True             True
3       AL        4              59.81         True             True
4       AL        5              32.81         True            False

   abortion_org_endorse  left_figure_endorse  right_figure_endorse  \
0                 False                False                 False
1                 False                False                 False
```

```
2                False                False                False
3                False                False                False
4                False                False                False

   political_figure_endorse  prog_org_endorse  cons_org_endorse
0                     False             False             False
1                     False             False             False
2                     False             False             False
3                     False             False             False
4                     False              True             False
```

Finally, we merge the census dataset with the endorsements/partisan lean dataset.

[14]:
```
district_full = pd.merge(left = district_partisan, right = census_data, on =␣
 ↪['state_ab', 'district'], how = 'left')
district_full['district'] = district_full['district'].replace('', '1')
state_name = district_full.pop('state_name')
district_full.insert(0, 'state_name', state_name)
district_full.head()
```

[14]:
```
  state_name state_ab district  abs_partisan_lean  any_endorse  \
0    Alabama       AL        1              28.61        False
1    Alabama       AL        2              30.97        False
2    Alabama       AL        3              31.37         True
3    Alabama       AL        4              59.81         True
4    Alabama       AL        5              32.81         True

   gun_org_endorse  abortion_org_endorse  left_figure_endorse  \
0            False                 False                False
1            False                 False                False
2             True                 False                False
3             True                 False                False
4            False                 False                False

   right_figure_endorse  political_figure_endorse  …  amer_indian_pop  \
0                 False                     False  …              0.0
1                 False                     False  …              0.0
2                 False                     False  …              0.0
3                 False                     False  …              0.0
4                 False                     False  …              0.0

   amer_indian_percent  nat_hawaiian_pop  nat_hawaiian_percent  \
0                  0.0               0.0                   0.0
1                  0.0               0.0                   0.0
2                  0.0               0.0                   0.0
3                  0.0               0.0                   0.0
4                  0.0               0.0                   0.0
```

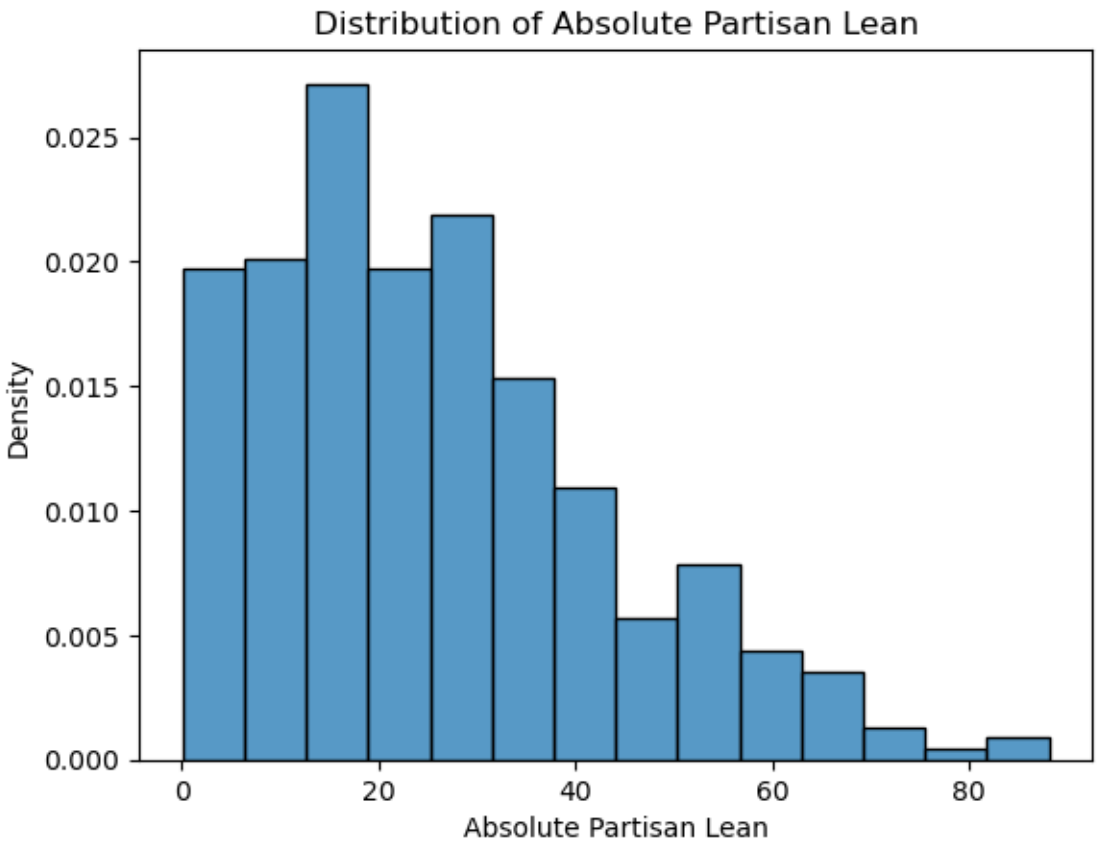
```
   other_race_pop  other_race_percent  two_more_race_pop  \
0          2884.0               0.005             7325.0
1          1818.0               0.004             7705.0
2          2448.0               0.005             6754.0
3          3529.0               0.007             8327.0
4          5852.0               0.011            12317.0

   two_more_race_percent  hispanic_pop  hispanic_percent
0                  0.013       11678.0             0.021
1                  0.015        9755.0             0.019
2                  0.012       12241.0             0.023
3                  0.016       11700.0             0.023
4                  0.022       14670.0             0.027

[5 rows x 59 columns]
```

1.3 EDA

[15]:
```
data = district_full
```

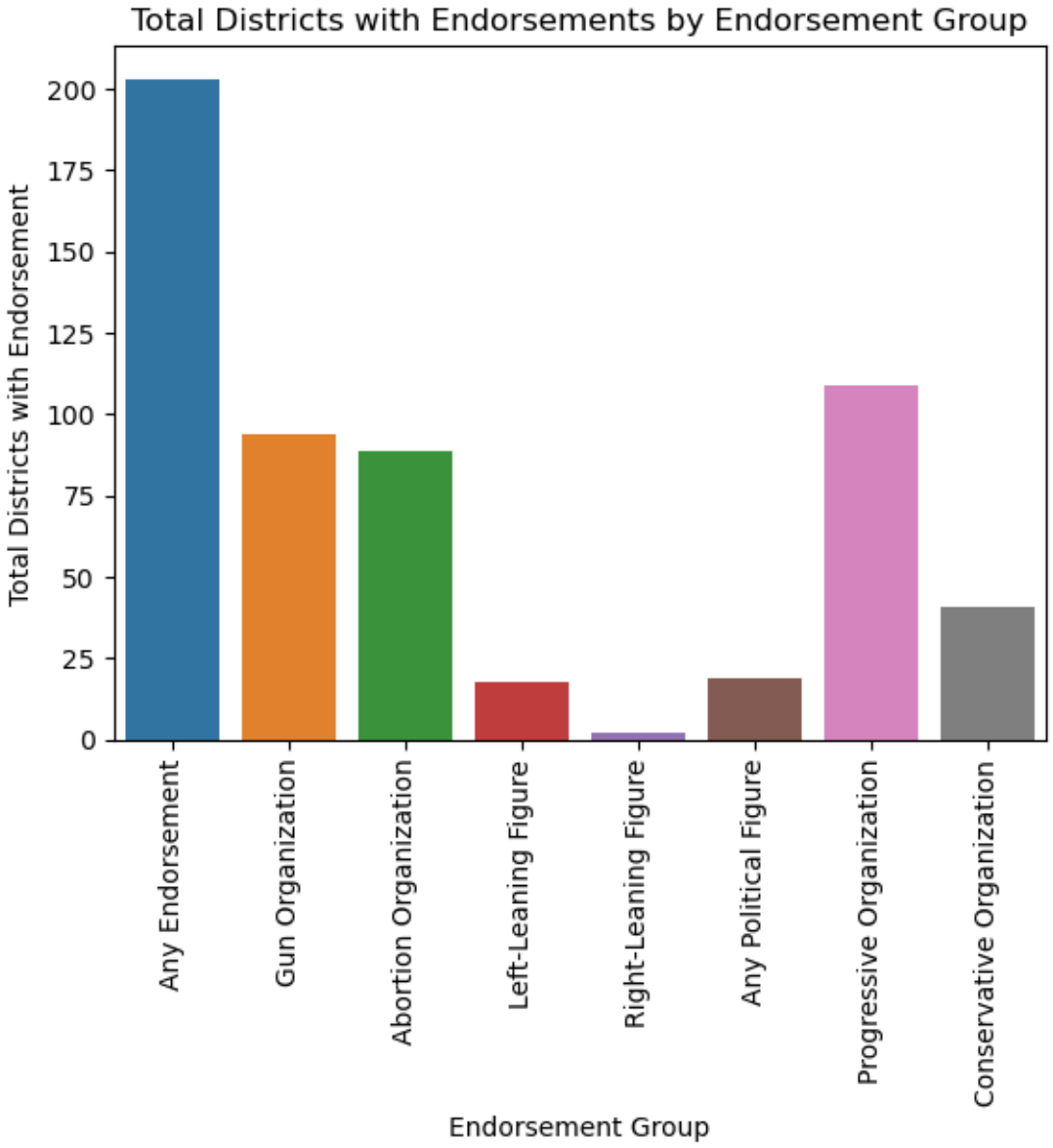
In the following sections of code, we create various visualizations for our EDA section.

[16]:
```
sns.histplot(data = data, x = 'abs_partisan_lean', stat = 'density')
plt.xlabel("Absolute Partisan Lean")
plt.title('Distribution of Absolute Partisan Lean')
plt.show()
```



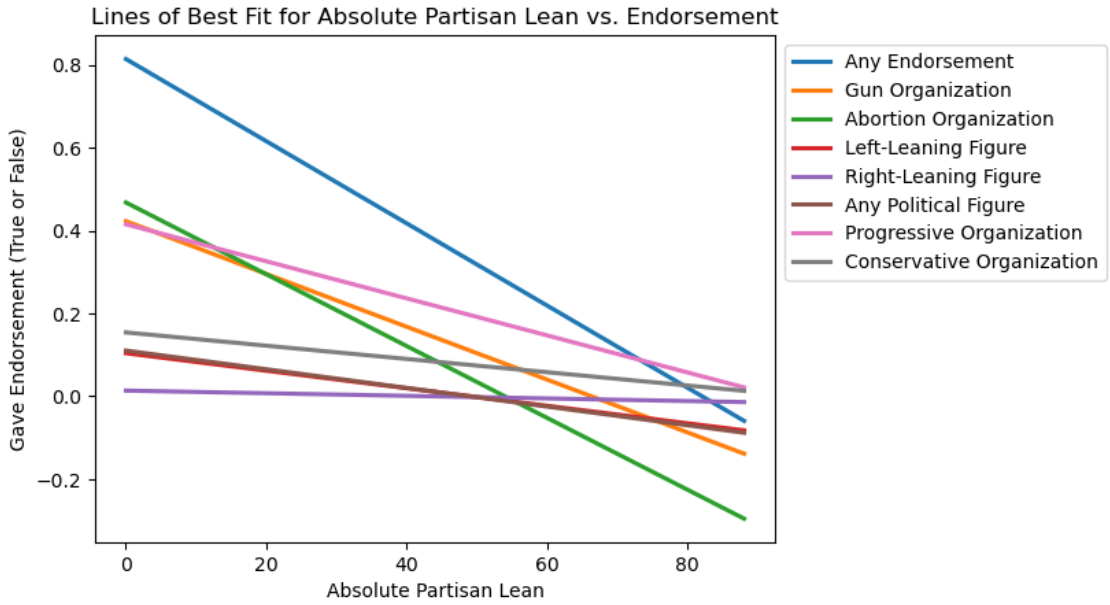
[17]:
```
g1 = data['any_endorse'].values.sum()
g2 = data['gun_org_endorse'].values.sum()
g3 = data['abortion_org_endorse'].values.sum()
g4 = data['left_figure_endorse'].values.sum()
g5 = data['right_figure_endorse'].values.sum()
g6 = data['political_figure_endorse'].values.sum()
g7 = data['prog_org_endorse'].values.sum()
g8 = data['cons_org_endorse'].values.sum()

names = ['Any Endorsement',
         'Gun Organization',
         'Abortion Organization',
         'Left-Leaning Figure',
         'Right-Leaning Figure',
         'Any Political Figure',
         'Progressive Organization',
         'Conservative Organization']
endorsements = [g1, g2, g3, g4, g5, g6, g7, g8]

sns.barplot(x = names, y = endorsements)
```

```
plt.xlabel("Endorsement Group")
plt.xticks(rotation = 90)
plt.ylabel('Total Districts with Endorsement')
plt.title('Total Districts with Endorsements by Endorsement Group')

plt.show()
```

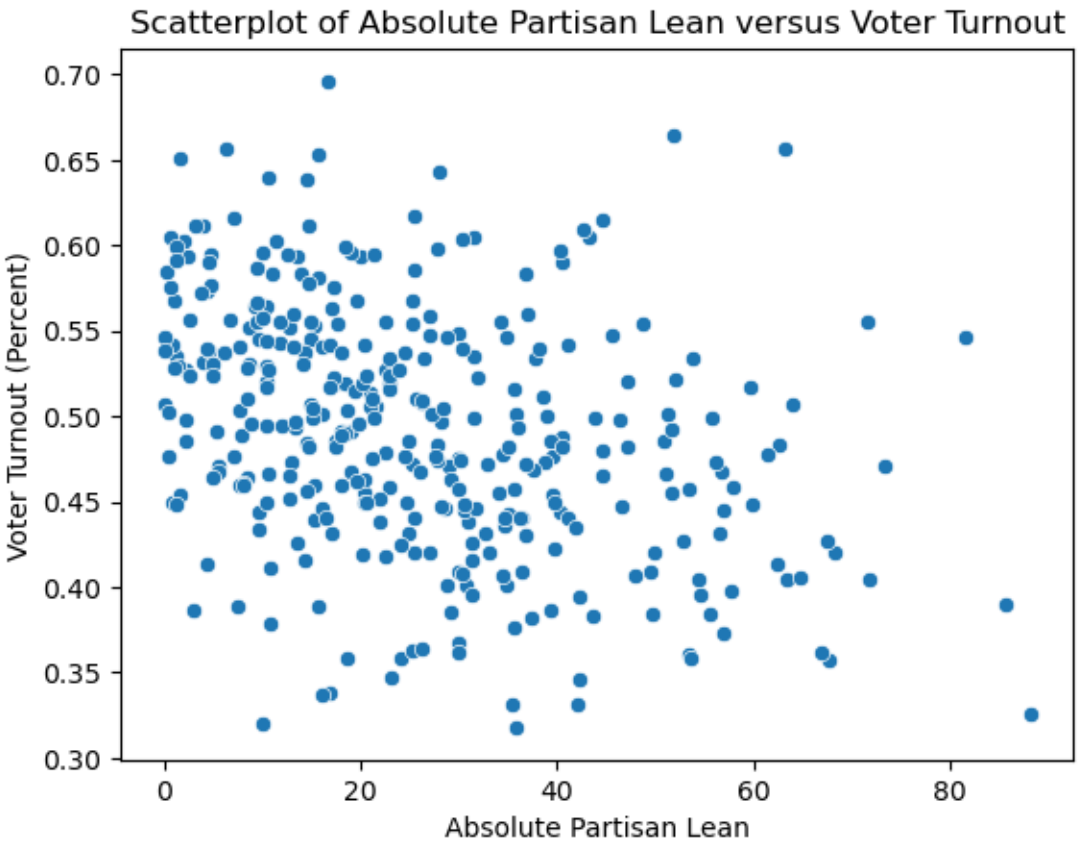


[18]:
```
groups = ['any_endorse',
          'gun_org_endorse',
          'abortion_org_endorse',
          'left_figure_endorse',
```

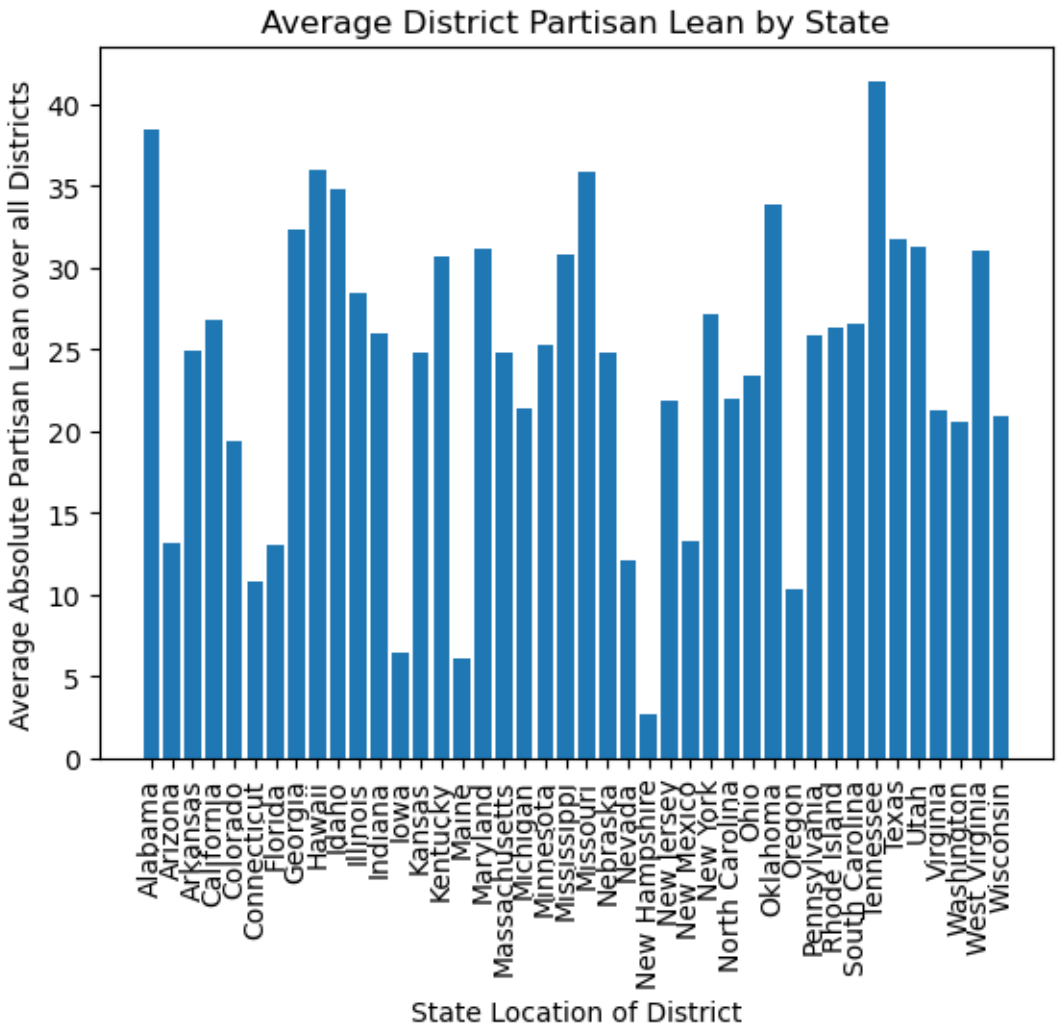
```
        'right_figure_endorse',
        'political_figure_endorse',
        'prog_org_endorse',
        'cons_org_endorse']
for i in np.arange(len(endorsements)):
    sns.regplot(data = data, x ='abs_partisan_lean', y = groups[i], scatter =␣
 ↪False, ci = False, label = names[i])
plt.xlabel('Absolute Partisan Lean')
plt.ylabel('Gave Endorsement (True or False)')
plt.title('Lines of Best Fit for Absolute Partisan Lean vs. Endorsement')
plt.legend(bbox_to_anchor=(1,1), loc="upper left")
plt.show()
```



[19]:
```
voter_turn_out = data[data['voting_percent'] > 0]
sns.scatterplot(data = voter_turn_out, x = 'abs_partisan_lean', y =␣
 ↪'voting_percent')
plt.xlabel('Absolute Partisan Lean')
plt.ylabel('Voter Turnout (Percent)')
plt.title('Scatterplot of Absolute Partisan Lean versus Voter Turnout')
plt.show()
```



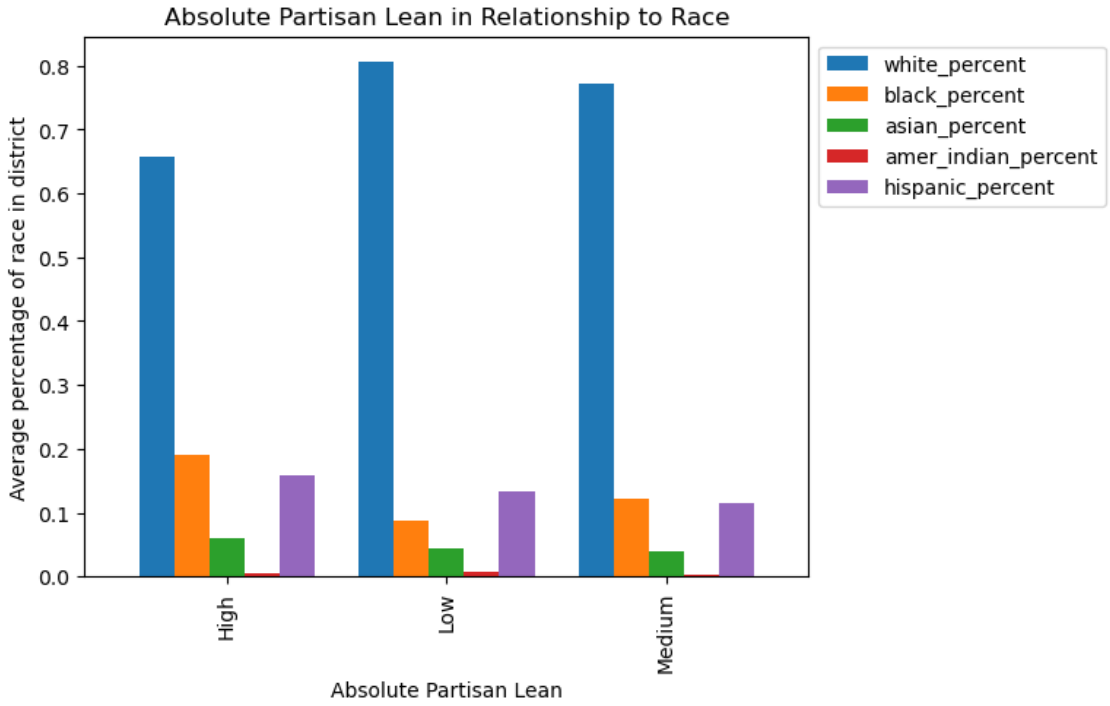
[20]:
```
stated = data.groupby(['state_name'], as_index=False).mean()
plt.bar(stated['state_name'], stated['abs_partisan_lean'])
plt.xlabel("State Location of District")
plt.xticks(rotation = 90)
plt.ylabel('Average Absolute Partisan Lean over all Districts')
plt.title('Average District Partisan Lean by State')
plt.show()
```



[21]:
```
race_data =␣
 ↪data[['abs_partisan_lean','white_percent','black_percent','asian_percent','amer_indian_perc

#cycle through data and make categories
categorical_lean = []
for i in race_data['abs_partisan_lean']:
    if i > 40:
        categorical_lean.append('High')
    elif i > 20:
        categorical_lean.append('Medium')
    else:
        categorical_lean.append('Low')
race_data['categorical_lean'] = categorical_lean
grouped_table = race_data.groupby('categorical_lean').mean().
 ↪drop(['abs_partisan_lean'], axis = 1)
```

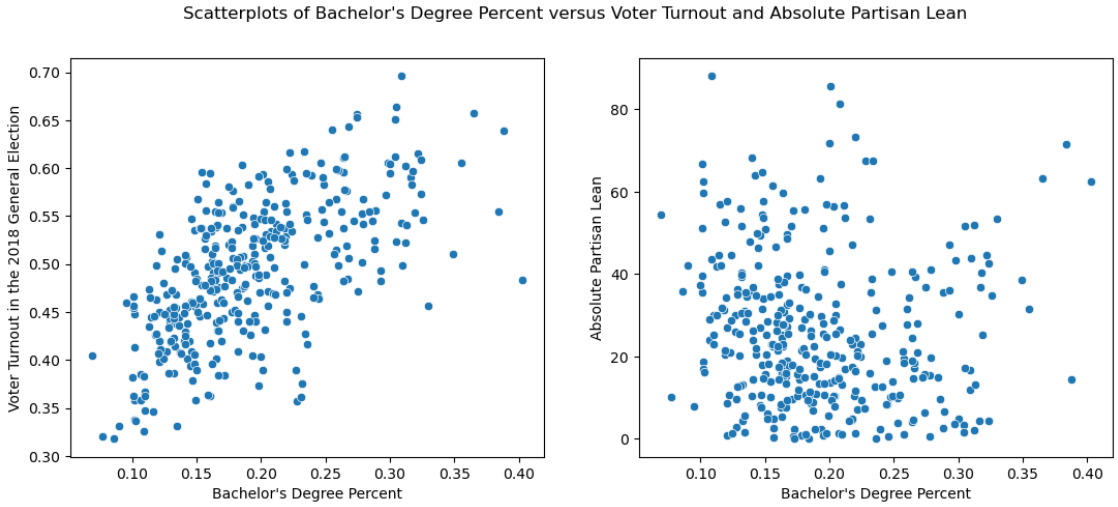
```
grouped_table.plot(kind = 'bar', width = 0.8)
plt.ylabel('Average percentage of race in district')
plt.xlabel('Absolute Partisan Lean')
plt.title('Absolute Partisan Lean in Relationship to Race')
plt.legend(bbox_to_anchor=(1,1), loc="upper left")
plt.show()
```

```
/tmp/ipykernel_41/52667240.py:12: 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-copy
  race_data['categorical_lean'] = categorical_lean
```



[22]:
```
fig, ax = plt.subplots(1,2, figsize = (13 , 5))
sns.scatterplot(data = voter_turn_out, x = 'bachelors_percent', y =␣
 ↪'voting_percent', ax = ax[0])
sns.scatterplot(data = voter_turn_out, x = 'bachelors_percent', y =␣
 ↪'abs_partisan_lean', ax = ax[1])
fig.suptitle("Scatterplots of Bachelor's Degree Percent versus Voter Turnout␣
 ↪and Absolute Partisan Lean")
```

```
ax[0].set(xlabel ="Bachelor's Degree Percent", ylabel = "Voter Turnout in the␣
 ↪2018 General Election")
ax[1].set(xlabel ="Bachelor's Degree Percent", ylabel = "Absolute Partisan␣
 ↪Lean")
plt.show()
```



1.4 Research Question 1

First we calculate the relevant correlations and p-values for each group.

[23]:
```
correlations = dict(zip(groups, np.zeros(len(groups))))
p_values = dict(zip(groups, np.zeros(len(groups))))
for group in groups:
    correlations[group], p_values[group] = pearsonr(data['abs_partisan_lean'],␣
 ↪data[group])
```

[24]:
```
correlations
```

[24]:
```
{'any_endorse': -0.3537265288303834,
 'gun_org_endorse': -0.2576598538885909,
 'abortion_org_endorse': -0.35672035866423635,
 'left_figure_endorse': -0.1724802021863193,
 'right_figure_endorse': -0.07520707064228685,
 'political_figure_endorse': -0.17902926866717725,
 'prog_org_endorse': -0.17273087107848376,
 'cons_org_endorse': -0.0896063556351526}
```

[25]:
```
p_values
```

[25]:
```
{'any_endorse': 3.869916590840938e-12,
 'gun_org_endorse': 6.477077722951401e-07,
 'abortion_org_endorse': 2.4738746476030977e-12,
 'left_figure_endorse': 0.0009681662127108682,
 'right_figure_endorse': 0.15272535710215238,
 'political_figure_endorse': 0.0006104499876722638,
 'prog_org_endorse': 0.0009515058513075095,
 'cons_org_endorse': 0.08823676709502899}
```

Then we define a function to print the rejected hypotheses for a given α for a naive approach, then with the Bonferroni correction and Benjamini-Hochberg procedure.

[26]:
```
def p_value_correction(alpha):
    naive_rejections = [group for group in p_values.keys() if p_values[group] <␣
 ↪alpha]
    print("Naive rejections:")
    print(*naive_rejections, sep = ", ")
    bonferroni_rejections = [group for group in p_values.keys() if␣
 ↪p_values[group] < (alpha/len(groups))]
    print("Bonferroni rejections:")
    print(*bonferroni_rejections, sep = ", ")
    #B-H correction
    sorted_p = sorted(p_values.values())
    m = len(groups)
    k = np.arange(1, m+1)
    threshold = max([sorted_p[i] for i in np.arange(0, m) if sorted_p[i] <=␣
 ↪k[i] * (alpha/m)])
    b_h_rejections = [group for group in p_values.keys() if p_values[group] <=␣
 ↪threshold]
    print("B-H rejections:")
    print(*b_h_rejections, sep = ", ")
```

[27]:
```
p_value_correction(0.05)
```

```
Naive rejections:
any_endorse, gun_org_endorse, abortion_org_endorse, left_figure_endorse,
political_figure_endorse, prog_org_endorse
Bonferroni rejections:
any_endorse, gun_org_endorse, abortion_org_endorse, left_figure_endorse,
political_figure_endorse, prog_org_endorse
B-H rejections:
any_endorse, gun_org_endorse, abortion_org_endorse, left_figure_endorse,
political_figure_endorse, prog_org_endorse
```

1.5 Research Question 2

First we bring in the OLS regressor from class, define the explanatory variables, and output the regression results.

[28]:
```
def fit_OLS_model(df, target_variable, explanatory_variables, intercept =␣
 ↪False):
    target = df[target_variable]
    inputs = df[explanatory_variables]
    if intercept:
        inputs = sm.add_constant(inputs)

    fitted_model = sm.OLS(target, inputs).fit()
    return(fitted_model)
explanatory_variables = list(data.columns[16:-1][::2])
explanatory_variables.append('abs_partisan_lean')
print('Explanatory variables:')
print(*explanatory_variables, sep = ", ")
data = data.fillna(0)
model = fit_OLS_model(data, 'voting_percent', explanatory_variables, intercept␣
 ↪= True)
print(model.summary())
```

```
Explanatory variables:
18-29_percent, 30-44_percent, 45-64_percent, 65_plus_percent, men_percent,
women_percent, poverty_percent, less_9th_percent, 9th-12th_percent,
high_school_percent, some_college_percent, associates_percent,
bachelors_percent, graduate_percent, white_percent, black_percent,
asian_percent, amer_indian_percent, nat_hawaiian_percent, other_race_percent,
two_more_race_percent, abs_partisan_lean
                            OLS Regression Results
==============================================================================
Dep. Variable:         voting_percent   R-squared:                       0.778
Model:                            OLS   Adj. R-squared:                  0.764
Method:                 Least Squares   F-statistic:                     54.29
Date:                Sun, 11 Dec 2022   Prob (F-statistic):           3.53e-97
Time:                        11:21:39   Log-Likelihood:                613.92
No. Observations:                 363   AIC:                            -1182.
Df Residuals:                     340   BIC:                            -1092.
Df Model:                          22
Covariance Type:            nonrobust
==============================================================================
=========
                             coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
---------
const                      0.0037      0.021      0.175      0.861      -0.038
0.045
18-29_percent             -3.0354      4.496     -0.675      0.500     -11.879
5.808
30-44_percent             -2.8194      4.502     -0.626      0.532     -11.674
```

```
6.035
45-64_percent            -2.5736      4.500     -0.572      0.568     -11.426
6.278
65_plus_percent          -2.6400      4.491     -0.588      0.557     -11.473
6.193
men_percent               9.6803      5.790      1.672      0.095      -1.709
21.069
women_percent             9.2430      5.775      1.600      0.110      -2.117
20.603
poverty_percent           0.0792      0.124      0.640      0.523      -0.164
0.323
less_9th_percent         -6.6106      3.281     -2.015      0.045     -13.064
-0.157
9th-12th_percent         -6.1326      3.314     -1.851      0.065     -12.651
0.386
high_school_percent      -5.9069      3.281     -1.800      0.073     -12.360
0.546
some_college_percent     -5.5180      3.280     -1.682      0.093     -11.970
0.934
associates_percent       -5.2172      3.281     -1.590      0.113     -11.670
1.236
bachelors_percent        -5.4308      3.290     -1.650      0.100     -11.903
1.041
graduate_percent         -5.3350      3.275     -1.629      0.104     -11.777
1.107
white_percent            -0.5814      0.666     -0.873      0.383      -1.892
0.729
black_percent            -0.5775      0.663     -0.871      0.384      -1.881
0.726
asian_percent            -0.8792      0.673     -1.306      0.193      -2.204
0.445
amer_indian_percent      -1.0924      0.635     -1.720      0.086      -2.342
0.157
nat_hawaiian_percent     -1.3743      0.829     -1.658      0.098      -3.005
0.256
other_race_percent       -0.5940      0.675     -0.880      0.379      -1.921
0.733
two_more_race_percent    -0.3145      0.758     -0.415      0.679      -1.806
1.177
abs_partisan_lean        -0.0002      0.000     -0.876      0.382      -0.000
0.000
==============================================================================
Omnibus:                      308.239   Durbin-Watson:                   1.422
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            18159.260
Skew:                          -3.062   Prob(JB):                         0.00
Kurtosis:                      37.104   Cond. No.                     1.58e+05
==============================================================================
```

```
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.58e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
/opt/conda/lib/python3.9/site-packages/statsmodels/tsa/tsatools.py:142:
FutureWarning: In a future version of pandas all arguments of concat except for
the argument 'objs' will be keyword-only
  x = pd.concat(x[::order], 1)
```

Here, we create the bins for "high" absolute partisan lean vs. "normal" lean.

[29]:
```
data['high_partisan_lean'] = pd.cut(data['abs_partisan_lean'], bins = [0, 40,␣
↪90], labels = [False, True])
```

We remove absolute partisan lean from our list of explanatory variables to create a list of only confounders.

[30]:
```
confounders = explanatory_variables
confounders.remove('abs_partisan_lean')
```

We define a model using the `causalinference` package, have it estimate propensity scores, trim any scores less than 0.1 and more than 0.9, then have it estimate the average treatment effect.

[31]:
```
causal = CausalModel(Y = data['voting_percent'].values, D =␣
↪data['high_partisan_lean'].values, X = data[confounders].values)
causal.est_propensity_s()
causal.trim()
causal.est_via_weighting()
print(causal.estimates)
```

```
Treatment Effect Estimates: Weighting

                     Est.       S.e.          z      P>|z|      [95% Conf. int.]
--------------------------------------------------------------------------------
           ATE      0.006      0.008      0.685      0.493     -0.010      0.022
```

```
/opt/conda/lib/python3.9/site-
packages/causalinference/estimators/weighting.py:23: FutureWarning: `rcond`
parameter will change to the default of machine precision times ``max(M, N)``
where M and N are the input matrix dimensions.
To use the future default and silence this warning we advise to pass
`rcond=None`, to keep using the old, explicitly pass `rcond=-1`.
  wlscoef = np.linalg.lstsq(Z_w, Y_w)[0]
```

We also use the approach from class, taking our propensity scores and feeding them into the IPW formula we learned.

[32]:
```
data['pscore'] = causal.propensity['fitted']
data_trimmed = data[(data['pscore'] > 0.1) & (data['pscore'] < 0.9)]
n = data_trimmed.shape[0]
treated = data_trimmed[data_trimmed['high_partisan_lean']==True]
control = data_trimmed[data_trimmed['high_partisan_lean']==False]
trimmed_ipw_estimate = (1/n)*sum(treated['voting_percent']/treated['pscore']) -␣
↪(1/n)*sum(control['voting_percent']/(1-control['pscore']))
print('Estimated ATE for high partisan lean on voting rate:')
print(trimmed_ipw_estimate)
```

```
Estimated ATE for high partisan lean on voting rate:
0.009817790802396809
```

We create a confidence interval for this ATE using a formula found online (bootstrapping proved to take too long to run).

[33]:
```
standard_error = np.sqrt(sum(data_trimmed['pscore']**2)/n)/np.sqrt(n)
lower_bound = trimmed_ipw_estimate - 1.96 * standard_error
upper_bound = trimmed_ipw_estimate + 1.96 * standard_error
print('Confidence interval of ATE')
print('(' + str(lower_bound) + ', ' + str(upper_bound) + ')')
```

```
Confidence interval of ATE
(-0.05544770802688631, 0.07508328963167993)
```