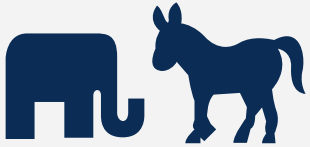


US Elections 2020

Economic and Demographic insights into voter behaviors and trends

Computer Programming and Data Management

Group: print("group name")

Analysis theme

How Economic, Social and Demographics factors influence voter behavior and election outcomes in the US and how elections affect them afterward.

Focus on 2020 elections

Index

01

US in 2020/21

Election Year Context

Importance of the 2020 elections

The 2020 US presidential election was a defining moment in American history, taking place amidst the unprecedented challenges of a global pandemic of COVID-19.

This election saw Donald Trump, the Republican incumbent, facing off against Joe Biden, the Democratic challenger. Their campaigns highlighted starkly different approaches to key issues, such as federal response to the pandemic, economic recovery plans, and racial justice protests.

The deeply polarized political climate, combined with social and economic factors, played a critical role in shaping voter behavior, ultimately leading to Biden's victory.

02

Economic factors

Occupation
Unemployment
Weekly Earnings
Consumer Price Index

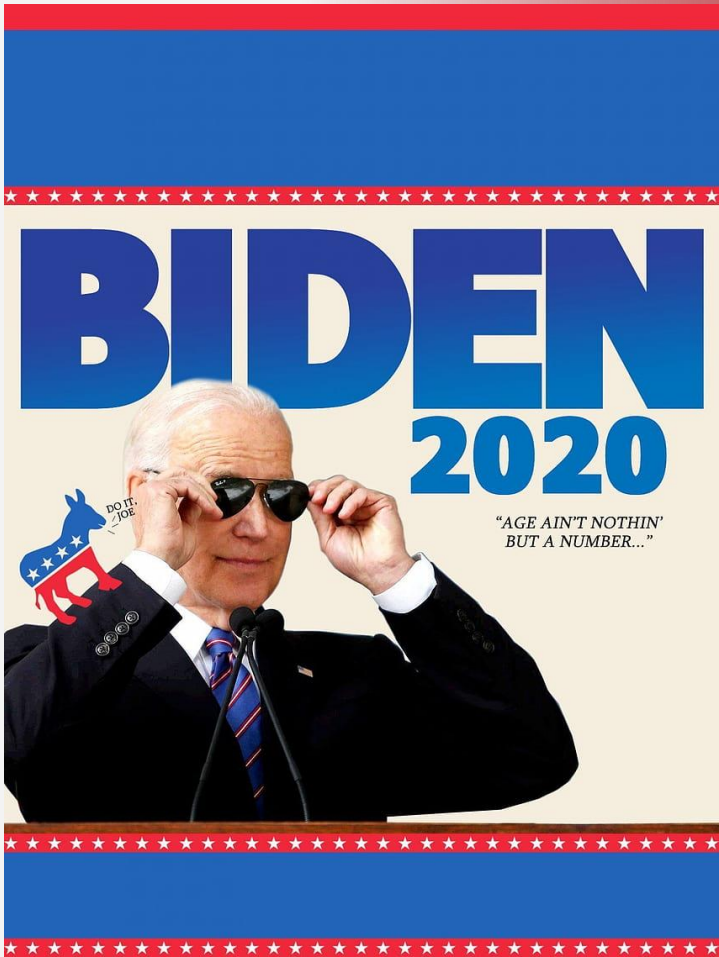
Biden economic proposal

During the 2020 elections, several economic proposal were put forward by Joe Biden. His plans emphasized job creation, clean energy, education, and healtcare, with significant attention to social justice and equity

Biden's overarching economic recovery strategy had three pillars:

- **Rescue**: immediate relief for those hit hardest by the COVID-19 pandemic;
- **Recovery**: stimulus measures to rebuild and stabilize the economy;
- **Rebuild for Resilience**: structural reforms to ensure long-term growth.

It is therefore interesting to analyze how the 2020 election, which saw Biden as president, influenced economic factors and how these changed in the periods following the elction.

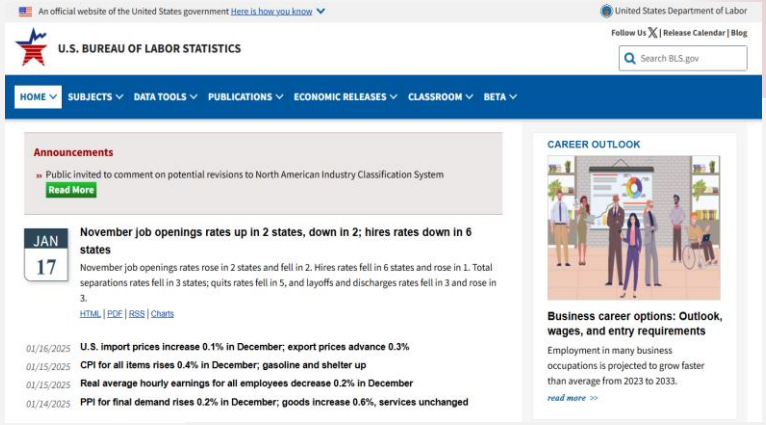


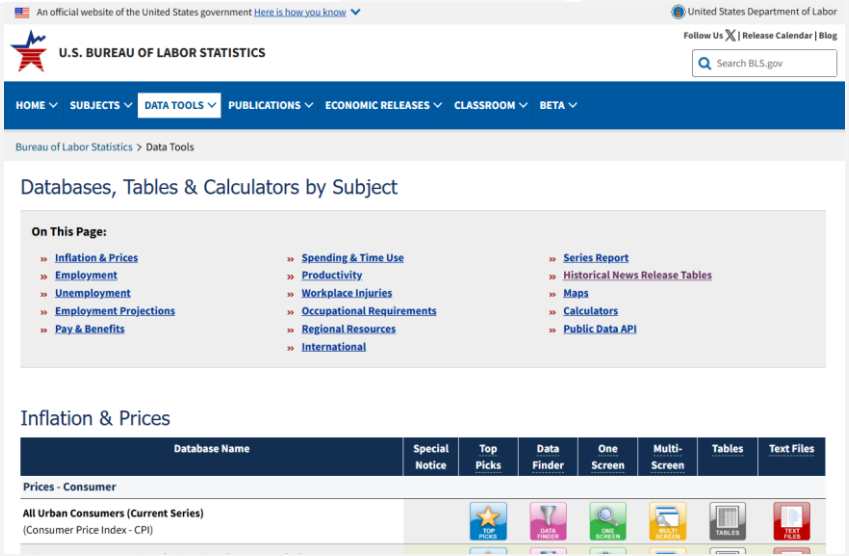
Datasets

For the economic part we have obtained the datasets useful for the analysis from the website of U.S. Bureau of Labor Statistics.

It is the US government's principal research agency in the broad field of economics and labors statistics and among the most important agencies.

https://www.bls.gov/





Occupation – Data cleaning

Data cleaning process for the occupation dataset.

```
work = pd.read_excel('/content/file/work.xlsx','tot')
display(work.head())
print('------------------------')
print(work.info())
print(work.isnull().sum())
```

	Occupation, race, and Hispanic or Latino ethnicity	Total	Unnamed: 2	Men	Unnamed: 4	Women	Unnamed: 6
0	NaN	2020.0	2021.0	2020.0	2021.0	2020.0	2021.0
1	TOTAL	NaN	NaN	NaN	NaN	NaN	NaN
2	Total, 16 years and over (in thousands)	147795.0	152581.0	78560.0	80829.0	69234.0	71752.0
3	Percent of total employed	100.0	100.0	100.0	100.0	100.0	100.0
4	Management, professional, and related occupations	43.1	42.4	39.1	38.5	47.5	46.9

```
------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18 entries, 0 to 17
Data columns (total 7 columns):
 #   Column                                             Non-Null Count  Dtype
---  ------                                             --------------  -----
 0   Occupation, race, and Hispanic or Latino ethnicity 17 non-null     object
 1   Total                                              17 non-null     float64
 2   Unnamed: 2                                         17 non-null     float64
 3   Men                                                17 non-null     float64
 4   Unnamed: 4                                         17 non-null     float64
 5   Women                                              17 non-null     float64
 6   Unnamed: 6                                         17 non-null     float64
dtypes: float64(6), object(1)
memory usage: 1.1+ KB
None
Occupation, race, and Hispanic or Latino ethnicity    1
Total                                                 1
Unnamed: 2                                            1
Men                                                   1
Unnamed: 4                                            1
Women                                                 1
Unnamed: 6                                            1
dtype: int64
```

The data contain information regarding:

- **Total population**
- **White**
- **Black**
- **Asian**
- **Hispanic or Latino**

Occupation – Data cleaning

```
xls_sheets = ['tot', 'white', 'black', 'asian', 'latino']

df_i = []
for i, sheet in enumerate(xls_sheets):
  df = pd.read_excel('/content/file/work.xlsx', sheet_name=sheet)
  df = df.rename(columns = {'Occupation, race, and Hispanic or Latino ethnicity': xls_sheets[i],
                            'Total': 'Total_2020', 'Unnamed: 2': 'Total_2021',
                            'Men': 'Men_2020', 'Unnamed: 4': 'Men_2021', 'Women':'Women_2020',
                            'Unnamed: 6': 'Women_2021'})
  df_i.append(df)

  df = df.drop(index=[0,1])
  print(df.info())
  print(df.isnull().sum())
  print('------------------------')
  df.to_csv(f'/content/file/{xls_sheets[i]}.csv', index=False)
```

From the occupation file excel we created a new worksheet for each ethnicity.

```
------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16 entries, 2 to 17
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   white        16 non-null     object
 1   Total_2020   16 non-null     float64
 2   Total_2021   16 non-null     float64
 3   Men_2020     16 non-null     float64
 4   Men_2021     16 non-null     float64
 5   Women_2020   16 non-null     float64
 6   Women_2021   16 non-null     float64
dtypes: float64(6), object(1)
```

```
------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16 entries, 2 to 17
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   black        16 non-null     object
 1   Total_2020   16 non-null     float64
 2   Total_2021   16 non-null     float64
 3   Men_2020     16 non-null     float64
 4   Men_2021     16 non-null     float64
 5   Women_2020   16 non-null     float64
 6   Women_2021   16 non-null     float64
dtypes: float64(6), object(1)
```

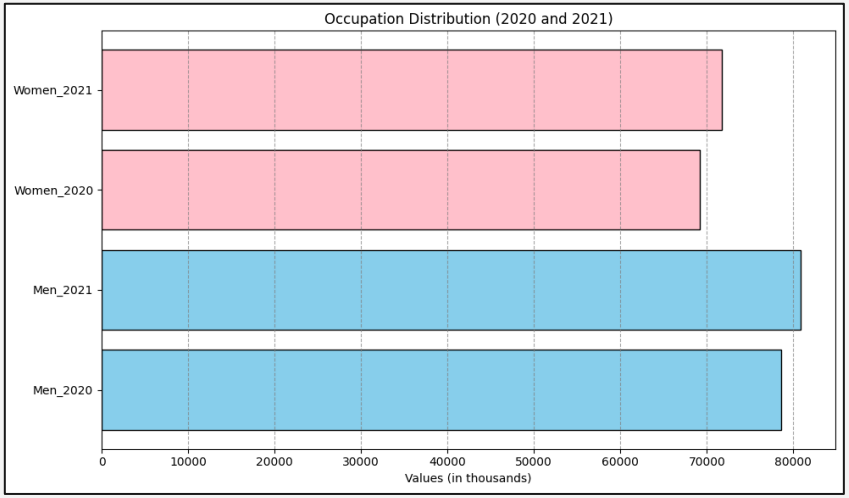
```
------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16 entries, 2 to 17
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   asian        16 non-null     object
 1   Total_2020   16 non-null     float64
 2   Total_2021   16 non-null     float64
 3   Men_2020     16 non-null     float64
 4   Men_2021     16 non-null     float64
 5   Women_2020   16 non-null     float64
 6   Women_2021   16 non-null     float64
dtypes: float64(6), object(1)
```

```
------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16 entries, 2 to 17
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   latino       16 non-null     object
 1   Total_2020   16 non-null     float64
 2   Total_2021   16 non-null     float64
 3   Men_2020     16 non-null     float64
 4   Men_2021     16 non-null     float64
 5   Women_2020   16 non-null     float64
 6   Women_2021   16 non-null     float64
dtypes: float64(6), object(1)
```

Occupation – Men and Women

This bar chart compares the occupation distribution by gender for the years 2020 and 2021.

It highlights a visible increase in employment levels for both men and women from 2020 to 2021, with men consistently showing higher absolute numbers in both years.



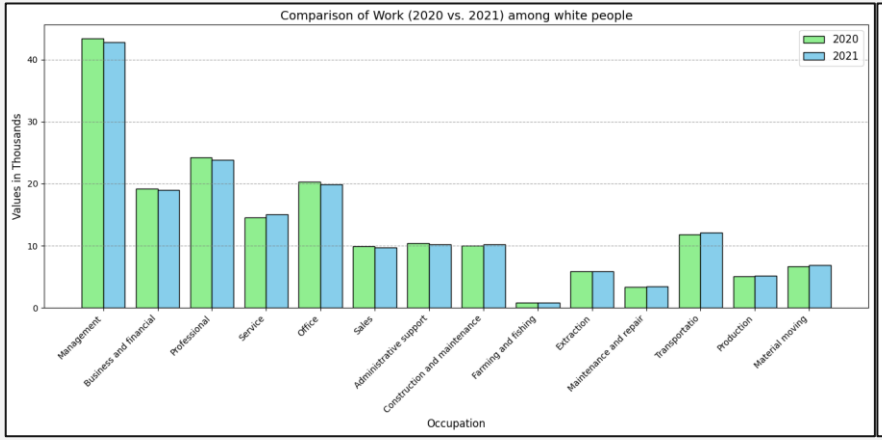

```
df_tot = pd.read_csv('/content/file/tot.csv')
df_white = pd.read_csv('/content/file/white.csv')
df_black = pd.read_csv('/content/file/black.csv')
df_asian = pd.read_csv('/content/file/asian.csv')
df_latino = pd.read_csv('/content/file/latino.csv')

occupation_data = df_tot.iloc[0, 3:7]
colors = ['skyblue' if 'Men' in label else 'pink' for label in occupation_data.index]

plt.figure(figsize = (10, 6))
plt.barh(occupation_data.index, occupation_data.values, color = colors, edgecolor = 'black' )
plt.title('Occupation Distribution (2020 and 2021)')
plt.grid(axis='x', linestyle='--', alpha=0.7, color = 'grey')
plt.xlabel('Values (in thousands)')

plt.tight_layout()
plt.show()
```

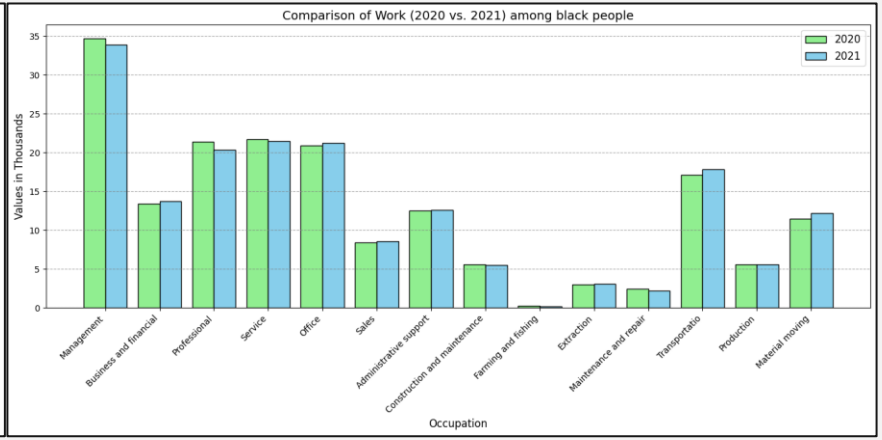
Occupation – Type of work

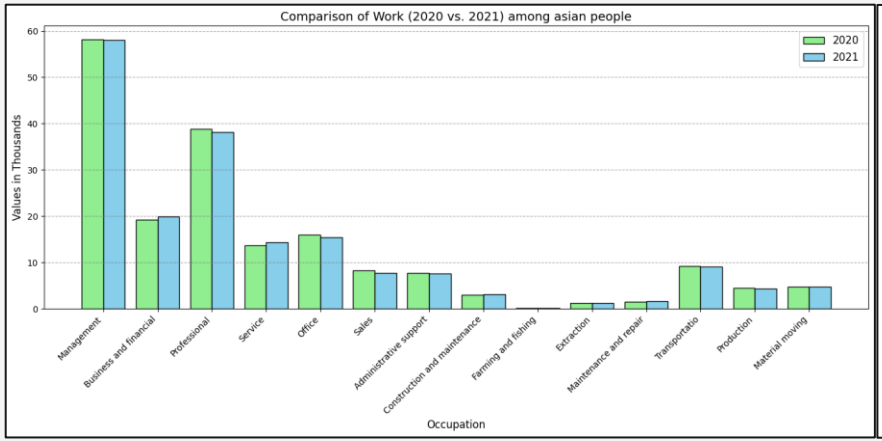
The following code was written to create a graph that compared the various ethnic groups, divided by type of work and by the two reference years: 2020 and 2021.

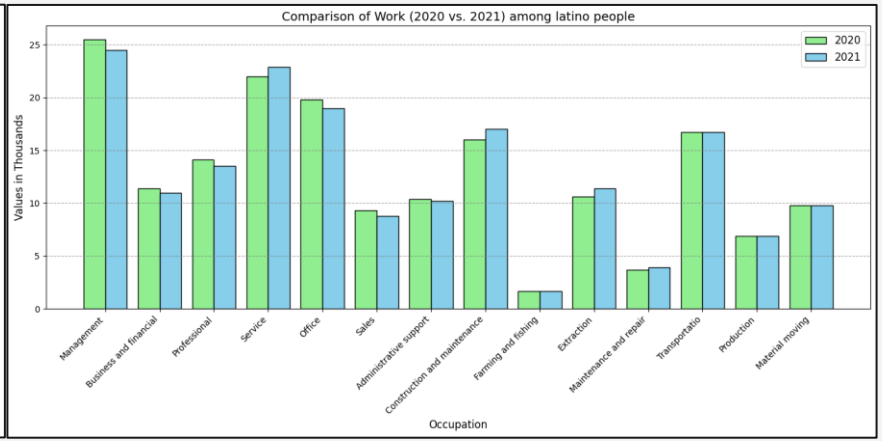
```
categories = ['Management, professional, and related occupations', 'Management, business, and financial operations occupations',
              'Professional and related occupations', 'Service occupations','Sales and office occupations', 'Sales and related occupations',
              'Office and administrative support occupations', 'Natural resources, construction, and maintenance occupations',
              'Farming, fishing, and forestry occupations', 'Construction and extraction occupations', 'Installation, maintenance, and repair occupations',
              'Production, transportation, and material moving occupations', 'Production occupations', 'Transportation and material moving occupations']
ethnicity = ["tot","white", "black", "asian", "latino"]
namex = ['Management',
         'Business and financial',
         'Professional',
         'Service',
         'Office',
         'Sales',
         'Administrative support',
         'Construction and maintenance',
         'Farming and fishing',
         'Extraction',
         'Maintenance and repair',
         'Transportatio',
         'Production',
         'Material moving']

for i, df in enumerate([df_tot, df_white, df_black, df_asian, df_latino]):

  filtered_df = df[df[ethnicity[i]].isin(categories)]

  bar_width = 0.4
  x = np.arange(len(filtered_df))
  values_2020 = filtered_df['Total_2020']
  values_2021 = filtered_df['Total_2021']

  plt.figure(figsize=(14, 7))
  plt.bar(x - bar_width/2, values_2020, bar_width, label='2020', color='lightgreen', edgecolor='black')
  plt.bar(x + bar_width/2, values_2021, bar_width, label='2021', color='skyblue', edgecolor='black')
  plt.xlabel('Occupation', fontsize=12)
  plt.ylabel('Values in Thousands', fontsize=12)
  plt.title(f'Comparison of Work (2020 vs. 2021) among {np.where(i==0, "total", ethnicity[i])} people', fontsize=14)
  plt.xticks(x, namex, rotation=45, ha='right', fontsize=10)
  plt.legend(loc='upper right', fontsize=12)
  plt.grid(axis = 'y', linestyle='--', alpha=0.7, color = 'grey')

  plt.tight_layout()
  plt.show()
```

Occupation – Type of work





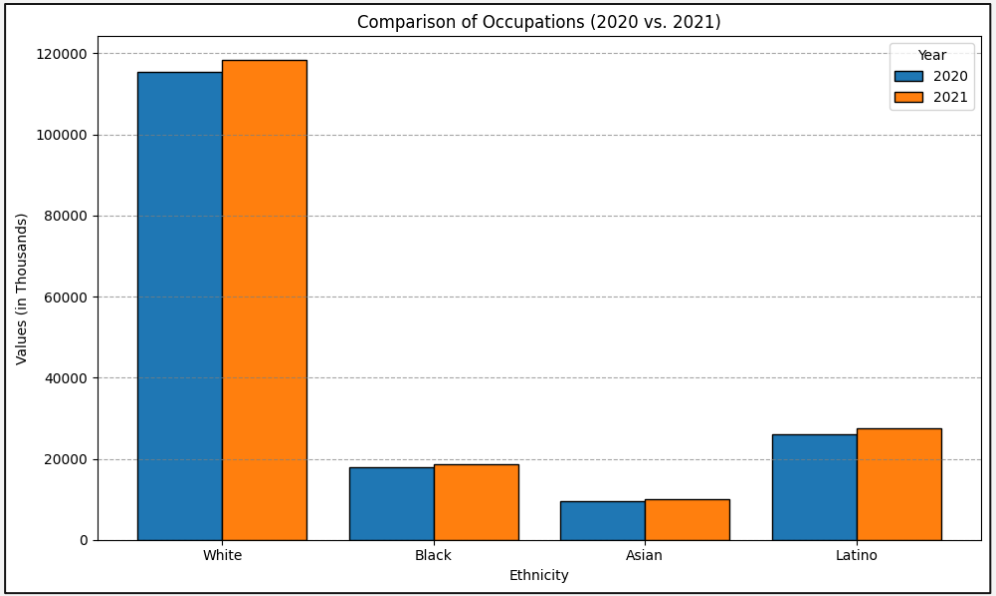




Occupation – Ethnicity summary

In the previous slide the changes for each job type for each ethnic group were analyzed.

In this graph we can observe the change in the number of workers from 2020 to 2021 based on ethnic group, regardless of gender and type of work.



Unemployment level – Data cleaning

```
df = pd.read_excel('/content/file/Unemployment Level.xlsx')

df = df.drop(range(0,11))
df.drop('Unnamed: 13', axis = 1, inplace = True)
df = df.rename(columns = {'Labor Force Statistics from the Current Population Survey': 'Year',
                          'Unnamed: 1': 'Jan',
                          'Unnamed: 2': 'Feb',
                          'Unnamed: 3': 'Mar',
                          'Unnamed: 4': 'Apr',
                          'Unnamed: 5': 'May',
                          'Unnamed: 6': 'Jun',
                          'Unnamed: 7': 'Jul',
                          'Unnamed: 8': 'Aug',
                          'Unnamed: 9': 'Sep',
                          'Unnamed: 10': 'Oct',
                          'Unnamed: 11': 'Nov',
                          'Unnamed: 12': 'Dec',})

df = df.set_index('Year')

df.dropna(inplace= True)
```

```
print('Number of unemployed people')
unemplyed_df = df.T
display(unemplyed_df)

unemplyed_df.to_csv('cleaned_UnemploymentLevel', index = True)
df1 = pd.read_csv('cleaned_UnemploymentLevel', index_col= 0)
```

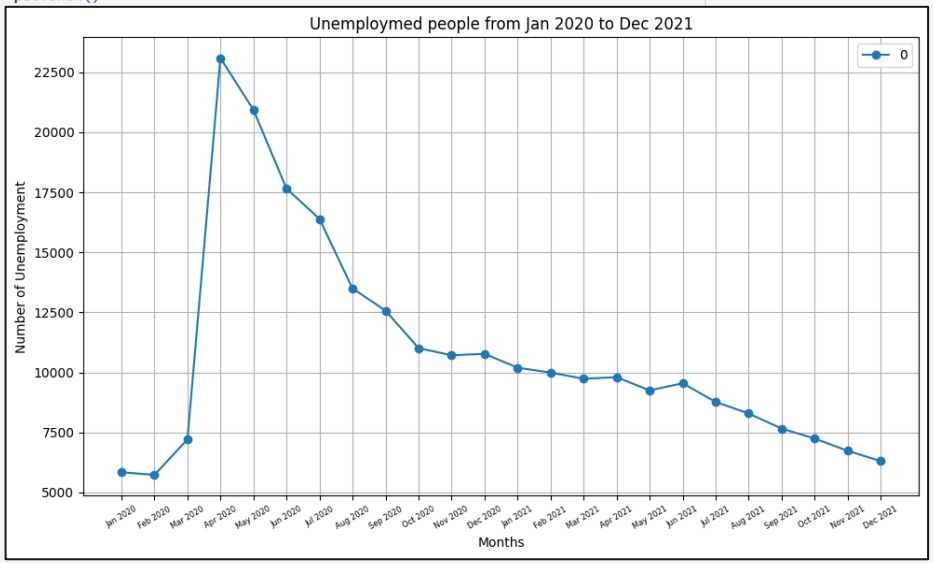
Year	2020	2021
Jan	5842	10196
Feb	5729	9992
Mar	7209	9734
Apr	23090	9801
May	20933	9250
Jun	17658	9547
Jul	16391	8770
Aug	13498	8288
Sep	12573	7659
Oct	11012	7244
Nov	10713	6733
Dec	10772	6305

This dataset contains information regarding the level of unemployment (in thousands) for each month of 2020 and 2021.

Unemployment level

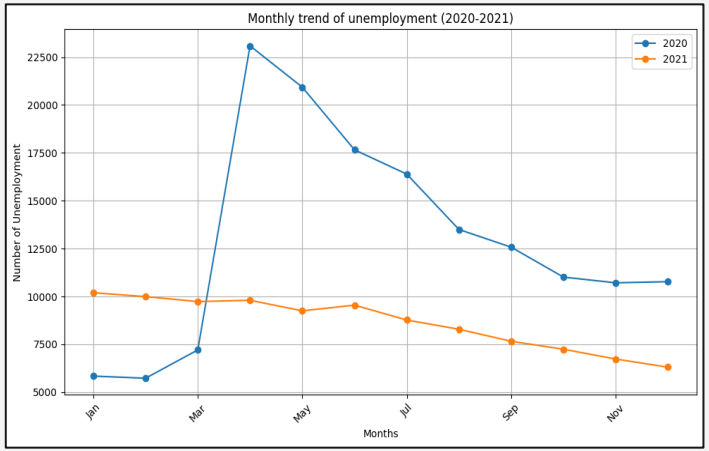
①

```
lst = df1.values.T.flatten().tolist()
Tot = pd.DataFrame(lst)

ax = Tot.plot(kind='line', marker='o')
ax.set_xlabel("Months")
ax.set_ylabel("Number of Unemployment")
ax.set_title("Unemploymed people from Jan 2020 to Dec 2021")
ax.grid(True)
plt.xticks(ticks = range(24),
                labels = [f'{month} {year}' for year in ['2020', '2021'] for month in ["Jan", "Feb", "Mar", "Apr", "May", "Jun",
                                                                                       "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]],

                rotation = 30,
                fontsize = 6)
plt.tight_layout()
plt.show()
```



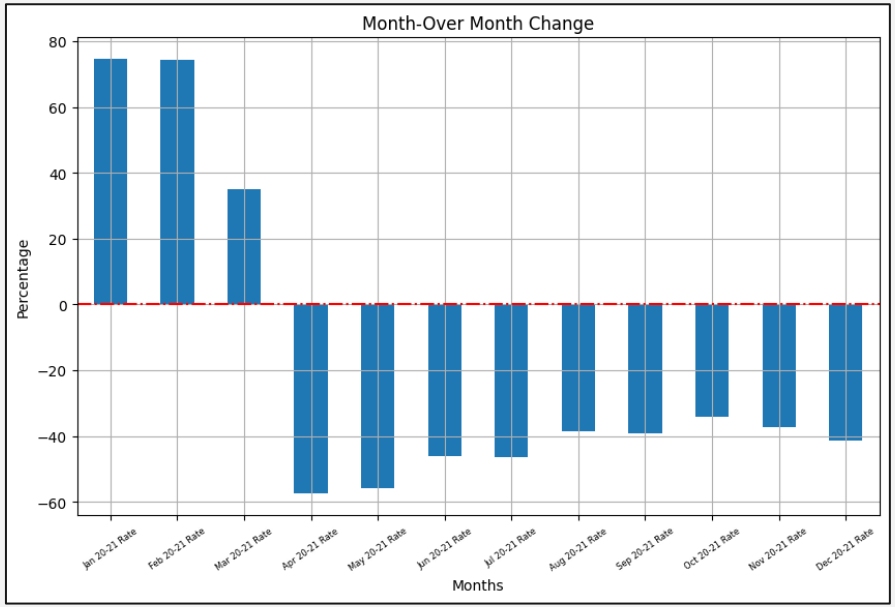
②

```
ax = df1.plot(kind='line', marker='o')
ax.set_xlabel("Months")
ax.set_ylabel("Number of Unemployment")
ax.set_title("Monthly trend of unemployment (2020-2021)")
ax.grid(True)
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



Unemployment level

```
df1 = df1.T
df1.loc['%'] = ((df1.loc['2021'] - df1.loc['2020']) / df1.loc['2020']) * 100
df1 = df1.T

ax = df1['%'].plot(kind = 'bar')
ax.set_xlabel('Months')
ax.set_ylabel('Percentage')
ax.set_title("Month-Over Month Change")
ax.grid(True)
plt.axhline(y = 0, color = 'r', linestyle = '-.')
plt.xticks(ticks = range(12),
           labels = [f'{i} 20-21 Rate' for i in ["Jan", "Feb", "Mar", "Apr", "May", "Jun", "Jul", "Aug", "Sep", "Oct", "Nov", "Dec"]],
           fontsize = 6,
          rotation = 35)
plt.show()
```



Here we can see a month-by-month comparison for the years 2020 and 2021.

- **Positive**: 2021 value is greater than 2020 value;
- **Negative**: 2020 value is greater than 2021 value

Unemployment rate – Data cleaning

```
State_unemployment_rates = pd.read_excel('/content/file/State_unemployment_rates.xlsx')
display(State_unemployment_rates.head())
print('------------------------')
print(State_unemployment_rates.info())
print(State_unemployment_rates.isnull().sum())
```

```
def change_columns():
  months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
  years = [2020, 2021]
  column_names = [f'{month}{year}' for year in years for month in months]
  return column_names

new_columns_names = change_columns()
State_unemployment_rates.columns = [State_unemployment_rates.columns[0]] + new_columns_names

State_unemployment_rates.to_csv(f'/content/file/State_unemployment_rates.csv', index = False)
display(State_unemployment_rates)
```

With this command we have abbreviated the name of the year columns.

We also analyzed the unemployment rate for each state and for each month for the years 2020 and 2021.

	State	Jan2020	Feb2020	Mar2020	Apr2020	May2020	Jun2020	Jul2020	Aug2020	Sep2020	...	Mar2021	Apr2021	May2021	Jun2021	Jul2021	Aug2021	Sep2021	Oct2021	Nov2021	Dec2021
0	Alabama	3.2	3.3	3.4	13.8	10.4	8.6	7.5	6.3	5.9	...	3.8	3.7	3.5	3.5	3.3	3.2	3.0	2.9	2.8	2.7
1	Alaska	5.4	5.5	5.5	11.7	11.8	11.2	11.1	8.6	7.9	...	7.0	7.0	6.8	6.8	6.4	6.2	5.9	5.7	5.5	5.3
2	Arizona	4.8	4.8	4.9	13.8	11.2	9.8	8.9	7.9	7.5	...	6.0	5.8	5.5	5.3	5.0	4.6	4.3	4.1	3.9	3.7
3	Arkansas	3.5	3.6	4.9	10.1	8.9	7.9	7.3	6.4	6.0	...	4.7	4.5	4.4	4.2	3.9	3.7	3.5	3.4	3.3	3.2
4	California	4.3	4.4	5.5	16.1	15.8	13.8	13.2	11.9	10.0	...	8.4	8.3	7.9	7.8	7.4	7.0	6.5	6.1	5.7	5.5
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
46	Virginia	2.8	2.9	3.2	12.0	10.0	8.9	8.2	7.2	6.6	...	4.5	4.4	4.2	4.0	3.8	3.5	3.3	3.1	3.0	2.9
47	Washington	3.7	3.8	5.2	16.7	13.4	11.5	10.4	8.8	8.1	...	6.0	5.7	5.5	5.4	5.2	5.0	4.7	4.5	4.2	4.1
48	West Virginia	5.3	5.3	5.4	15.8	12.4	10.5	9.4	8.1	7.5	...	5.9	5.7	5.5	5.4	5.1	4.9	4.6	4.4	4.2	4.0
49	Wisconsin	3.1	3.1	3.0	14.0	10.6	8.7	7.7	6.4	5.8	...	4.4	4.3	4.1	4.0	3.8	3.6	3.4	3.3	3.1	3.0
50	Wyoming	4.4	4.6	4.8	5.1	8.7	7.3	6.8	6.2	5.9	...	5.2	5.0	4.9	4.7	4.5	4.3	4.1	3.9	3.7	3.6

Unemployment rate - Code

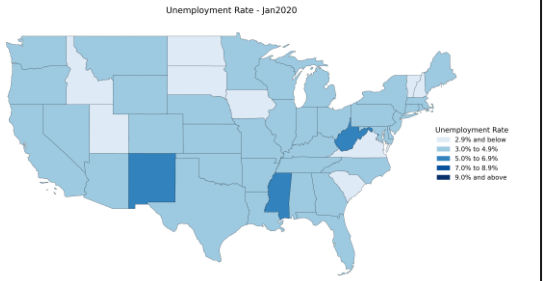
①

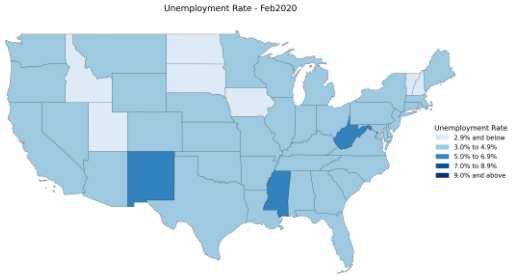
```
data = State_unemployment_rates

def download_USA_maps(url, extract_to):
  # Download and extract shapefile data from the URL
  zip_path = Path('temp_shapefile.zip')
  response = requests.get(url)
  zip_path.write_bytes(response.content)

  with ZipFile(zip_path, 'r') as zip_ref:
    zip_ref.extractall(extract_to)

  zip_path.unlink()

# URL of the shapefile and directory where store it
shapefile_url = 'https://www2.census.gov/geo/tiger/GENZ2021/shp/cb_2021_us_state_20m.zip'
shapefile_dir = Path("usa_shapefiles")
shapefile_dir.mkdir(exist_ok = True)

download_USA_maps(shapefile_url, shapefile_dir)

shapefile_path = shapefile_dir / 'cb_2021_us_state_20m.shp'

gdf = gpd.read_file(shapefile_path)

excluded_states = ["AS", "GU", "MP", "PR", "VI"]
gdf = gdf[~gdf["STUSPS"].isin(excluded_states)]

alaska = gdf[gdf["STUSPS"] == "AK"].scale(0.35, 0.35).translate(-4000000, -2500000)
hawaii = gdf[gdf["STUSPS"] == "HI"].scale(1.5, 1.5).translate(5200000, -1400000)
gdf = gdf[~gdf["STUSPS"].isin(["AK", "HI"])]

gdf = pd.concat([gdf, alaska, hawaii])

data.rename(columns = {'State': 'NAME'}, inplace = True)
merged = gdf.merge(data, on = 'NAME', how = 'left')

output_dir = Path('us_unemployment_maps')
output_dir.mkdir(exist_ok = True)

bins = [0, 2.9, 4.9, 6.9, 8.9, 100]
colors = ["#deebf7", "#9ecae1", "#3182bd", "#08519c", "#08306b"]
cmap = ListedColormap(colors)
norm = BoundaryNorm(bins, cmap.N)
```

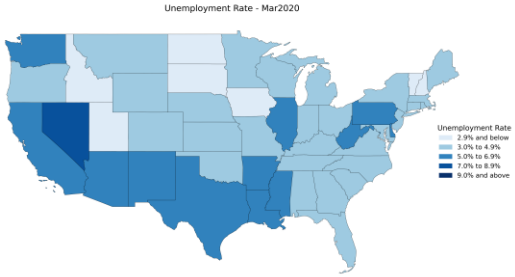
②

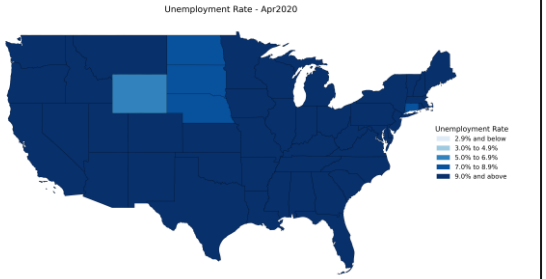
```
months = data.columns[1:]
for month in months:
  fig, ax = plt.subplots(1, 1, figsize=(25, 15))

  merged.plot(column = month,
              cmap = cmap,
              norm = norm,
              ax = ax,
              linewidth = 0.5,
              missing_kwds = {'color': 'lightgrey', 'label': 'No data'},
              edgecolor = 'black')

  ax.set_title(f'Unemployment Rate - {month}', fontsize = 24, pad = 20)
  ax.axis('off')

  legend_labels = [
      "2.9% and below",
      "3.0% to 4.9%",
      "5.0% to 6.9%",
      "7.0% to 8.9%",
      "9.0% and above",
  ]
  legend_handles = [
      mpatches.Patch(color=colors[i], label=legend_labels[i]) for i in range(len(colors))
  ]
  ax.legend(
      handles=legend_handles,
      title="Unemployment Rate",
      loc="center left",
      bbox_to_anchor=(0.9, 0.5),
      fontsize=18,
      title_fontsize=20,
      frameon=False
  )

  map_path = output_dir / f'Unemployment_Rate_{month}.png'
  plt.savefig(map_path, dpi = 300)
  plt.close()

print(f'Maps saved in: {output_dir}')
```

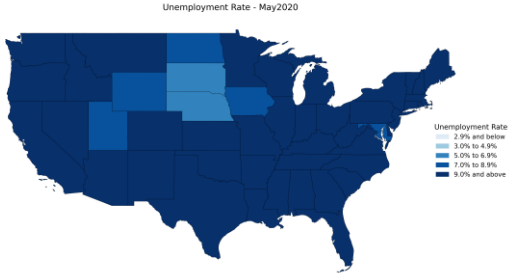
Unemployment rate - 2020

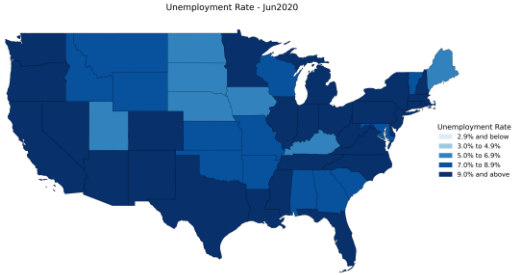




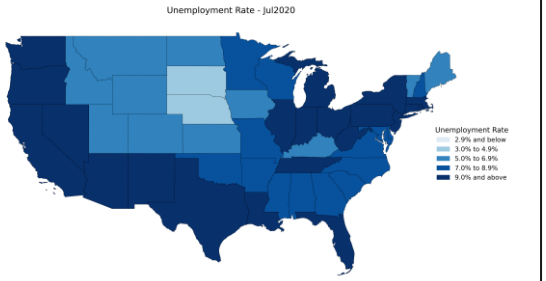


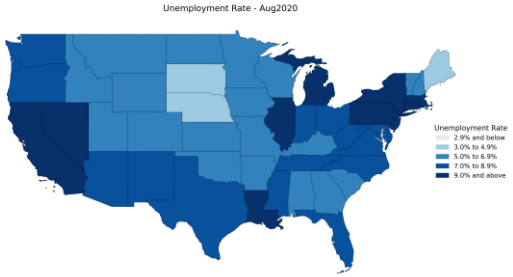


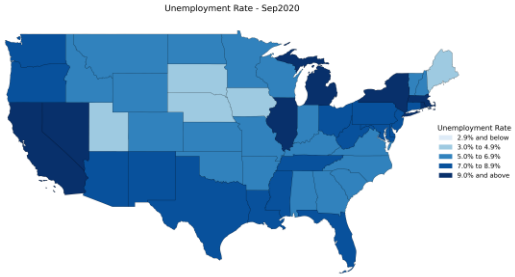


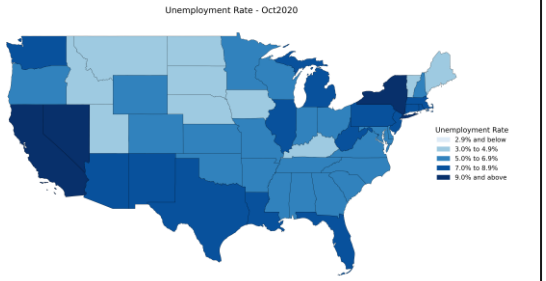


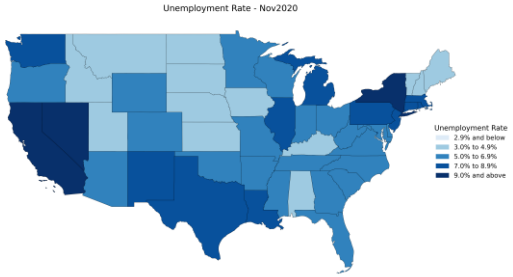
Unemployment rate - 2020

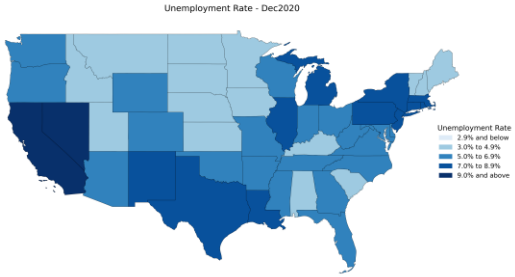




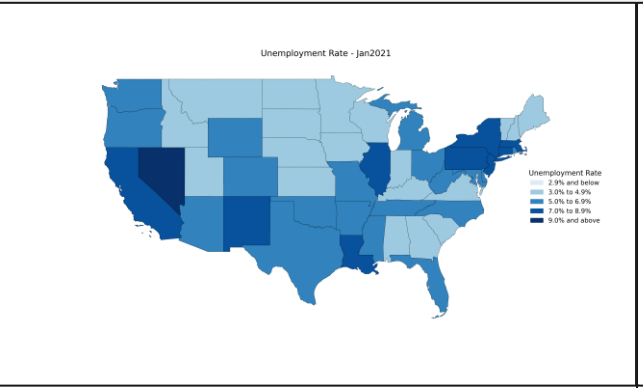


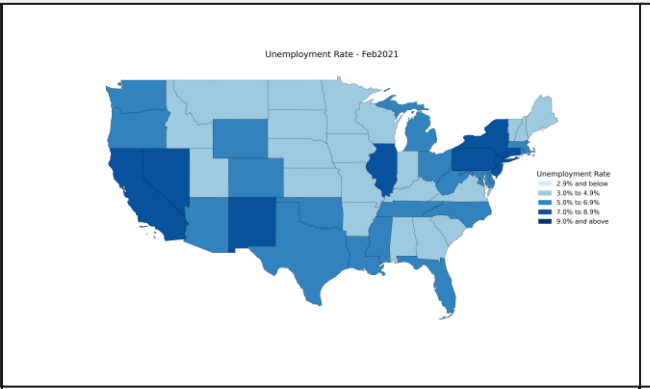


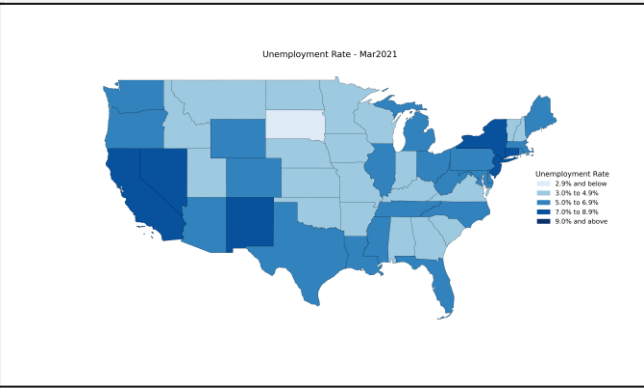


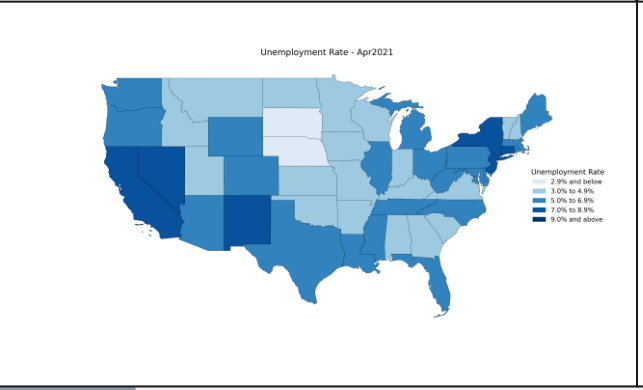


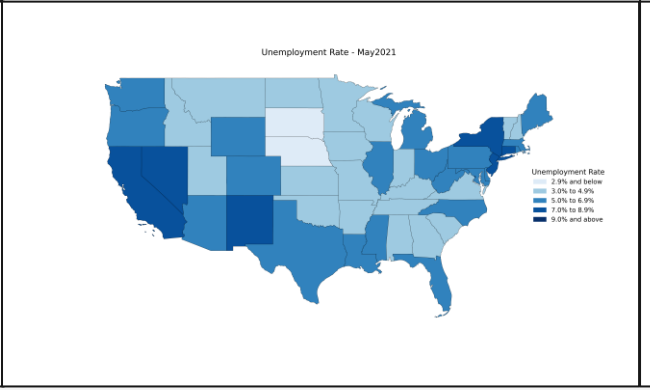
Unemployment rate - 2021

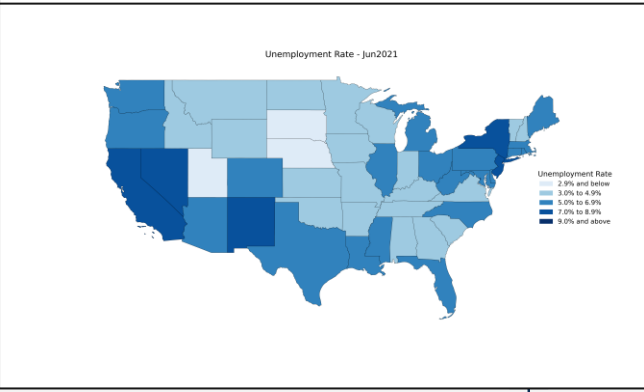




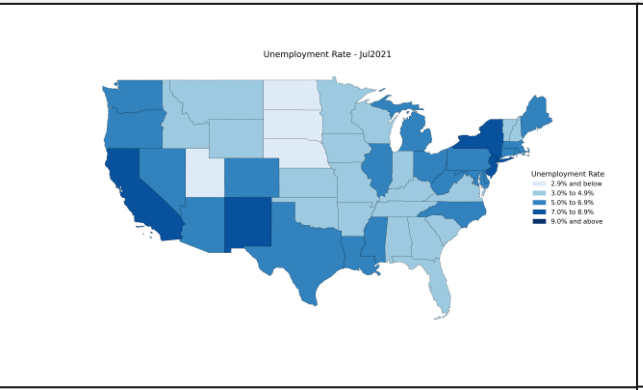


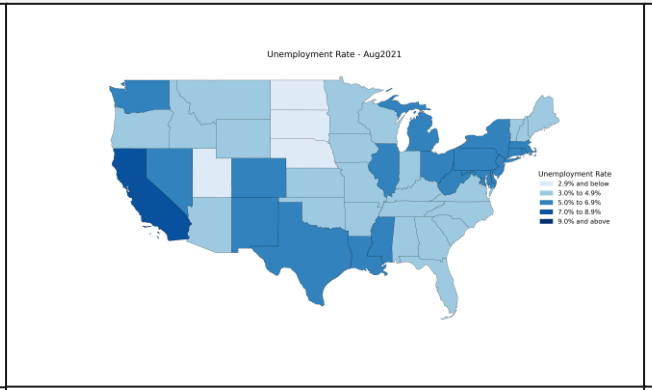


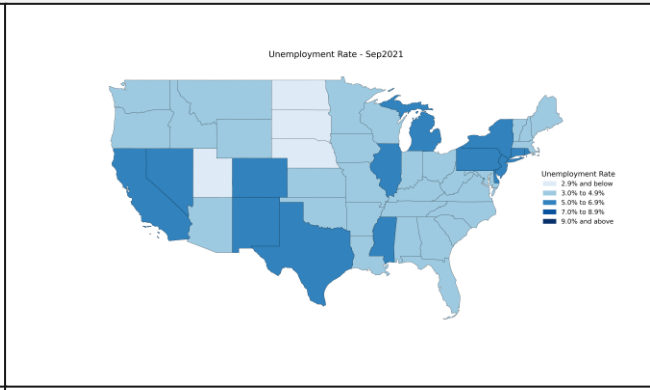


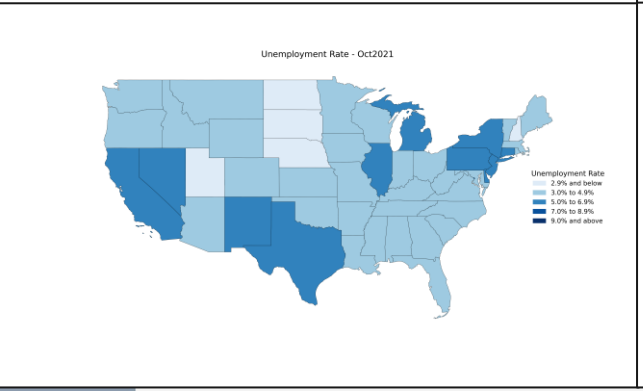


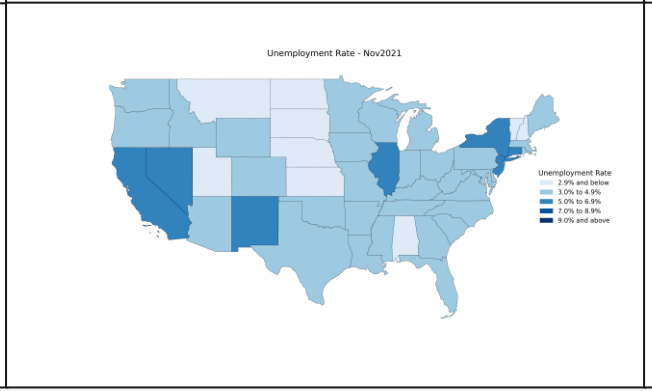
Unemployment rate - 2021

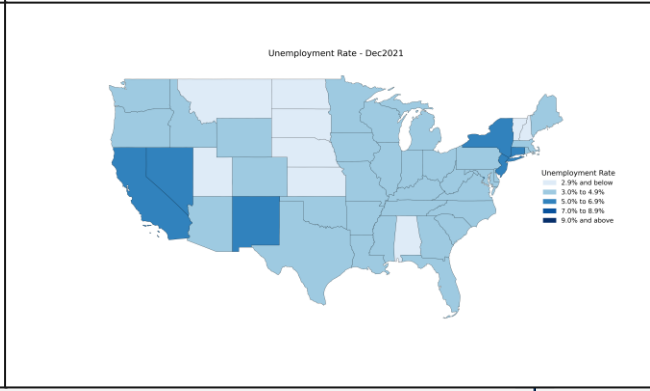












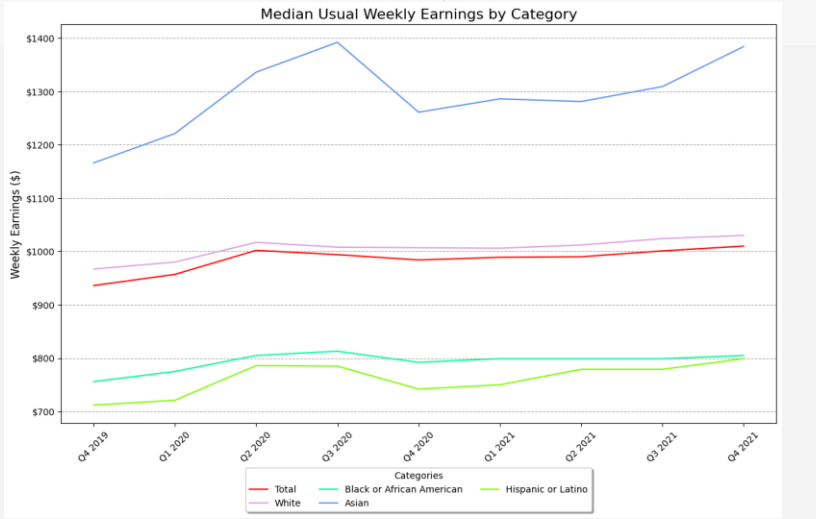
Weekly Earnings

```
Weekly_Earnings = pd.read_excel('/content/file/Weekly_Earnings.xlsx')
display(Weekly_Earnings.head())
print('------------------------')
print(Weekly_Earnings.info())
print(Weekly_Earnings.isnull().sum())
```

```
Weekly_Earnings.to_csv(f'/content/file/Weekly_Earnings.csv', index = False)
display(Weekly_Earnings)
```

	Quarter	Total	White	Black or African American	Asian	Hispanic or Latino
0	Q4 2019	936	967	756	1166	712
1	Q1 2020	957	980	775	1221	721
2	Q2 2020	1002	1017	805	1336	786
3	Q3 2020	994	1008	813	1392	785
4	Q4 2020	984	1007	792	1261	742
5	Q1 2021	989	1006	799	1286	750
6	Q2 2021	990	1012	799	1281	779
7	Q3 2021	1001	1024	799	1309	779
8	Q4 2021	1010	1030	805	1384	799

```
quarters = ['Q4 2019', 'Q1 2020', 'Q2 2020', 'Q3 2020', 'Q4 2020', 'Q1 2021', 'Q2 2021', 'Q3 2021', 'Q4 2021']
categories = ['Total', 'White', 'Black or African American', 'Asian', 'Hispanic or Latino']
colors = ['red', 'plum', 'mediumspringgreen', 'cornflowerblue', 'lawngreen']
values = Weekly_Earnings[Weekly_Earnings['Quarter'].isin(quarters)]
plt.figure(figsize=(12, 8))

for i, category in enumerate(categories):
  plt.plot(values['Quarter'], values[category], label = category, color = colors[i])

plt.title('Median Usual Weekly Earnings by Category', fontsize = 16)
plt.xlabel('Quarter', fontsize = 12)
plt.ylabel('Weekly Earnings ($)', fontsize = 12)
plt.xticks(rotation=45)
plt.grid(axis = 'y', linestyle = '--', alpha = 0.7, color = 'grey')

plt.gca().get_yaxis().set_major_formatter(plt.FuncFormatter(lambda x, _: f'${int(x)}'))

plt.legend(title = 'Categories', loc = 'upper center', bbox_to_anchor = (0.5, -0.1), fancybox = True, shadow = True, ncol = 3)

plt.tight_layout()
plt.show()
```



As we can see from the graph, only Asians have had a substantial change in weekly earnings after covid.

Earnings per State

```
Earnings_Per_State = pd.read_excel('/content/file/Earnings_Per_State.xlsx')
display(Earnings_Per_State.head())
print('-------------------------')
print(Earnings_Per_State.info())
print(Earnings_Per_State.isnull().sum())
```

```
Earnings_Per_State.to_csv(f'/content/file/Earnings_Per_State.csv', index = False)
display(Earnings_Per_State)
```

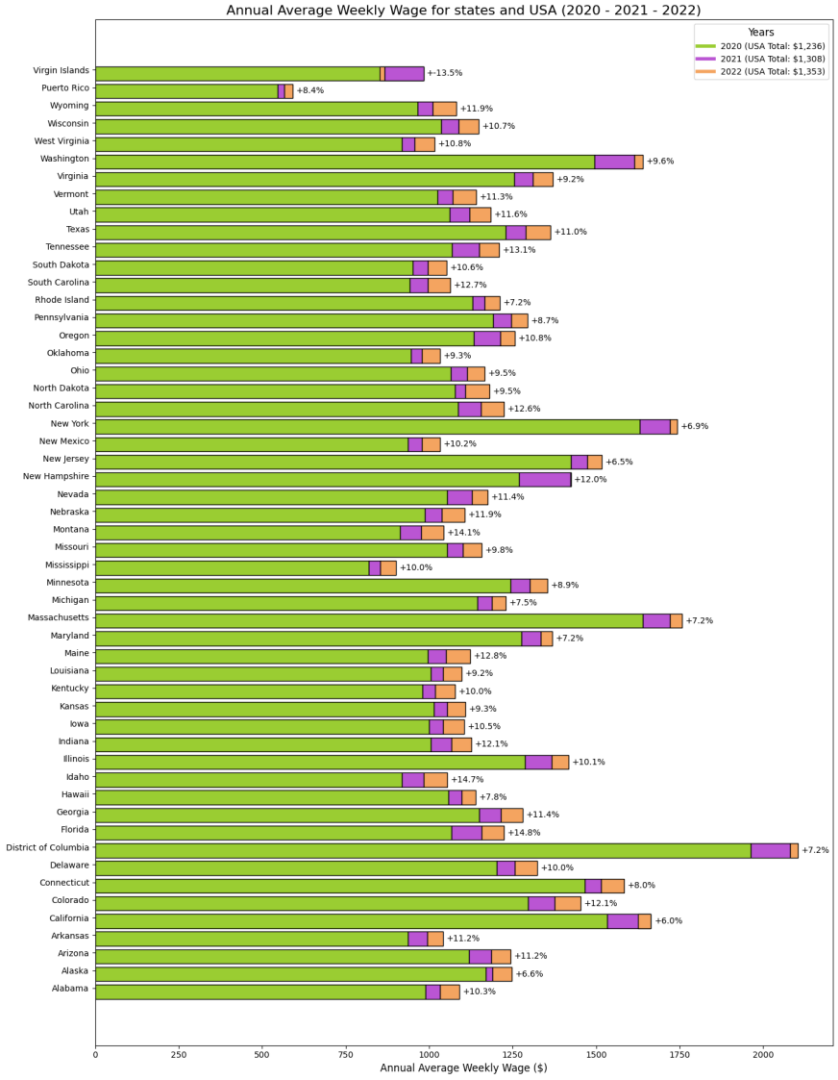
	State	Annual Average Weekly Wage (2020)	Annual Average Weekly Wage (2021)	Annual Average Weekly Wage (2022)
0	U.S. TOTAL	1236	1308	1353
1	Alabama	989	1032	1091
2	Alaska	1170	1189	1247
3	Arizona	1119	1187	1244
4	Arkansas	937	994	1042
...	...	...	...	...
49	West Virginia	918	956	1017
50	Wisconsin	1037	1089	1148
51	Wyoming	966	1011	1081
52	Puerto Rico	546	566	592
53	Virgin Islands	984	867	851

①

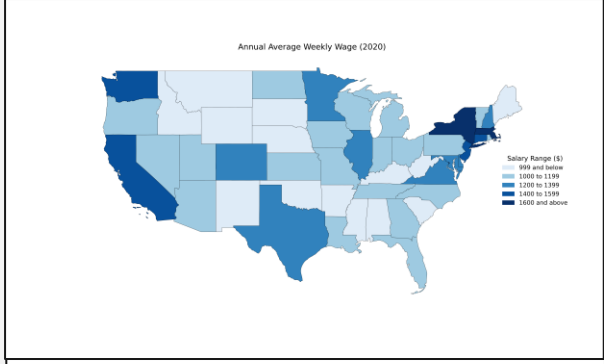
```
data = Earnings_Per_State

USA_data = data.iloc[0, 1:].values
states_data = data.iloc[1:]

states = states_data['State']
values_2020 = states_data['Annual Average Weekly Wage (2020)']
values_2021 = states_data['Annual Average Weekly Wage (2021)'] - states_data['Annual Average Weekly Wage (2020)']
values_2022 = states_data['Annual Average Weekly Wage (2022)'] - states_data['Annual Average Weekly Wage (2021)']

increments_rate = (
    (states_data['Annual Average Weekly Wage (2022)'] - states_data['Annual Average Weekly Wage (2020)'])
    / states_data['Annual Average Weekly Wage (2020)'] * 100
)

colors = ['yellowgreen', 'mediumorchid', 'sandybrown']
bar_width = 0.4

fig, ax = plt.subplots(figsize = (14, 18))
y_positions = np.arange(len(states))

ax.barh(y_positions, values_2020, color = colors[0], edgecolor = 'black', label = '2020')
ax.barh(y_positions, values_2021, left = values_2020, color = colors[1], edgecolor = 'black', label = '2021')
ax.barh(y_positions, values_2022, left = values_2020 + values_2021, color = colors[2], edgecolor = 'black', label = '2022')

for i, increments in enumerate(increments_rate):
    if states.iloc[i] == "Virgin Islands":
        text_position = values_2020.iloc[i] + values_2021.iloc[i] + values_2022.iloc[i] + 140
    elif states.iloc[i] == "California":
      text_position = values_2020.iloc[i] + values_2021.iloc[i] + values_2022.iloc[i] + 50
    else:
        text_position = values_2020.iloc[i] + values_2021.iloc[i] + values_2022.iloc[i] + 10

    ax.text(
        text_position,
        y_positions[i],
        f"+{increments:.1f}%",
        va='center', ha='left', fontsize=10, color='black'
    )
```

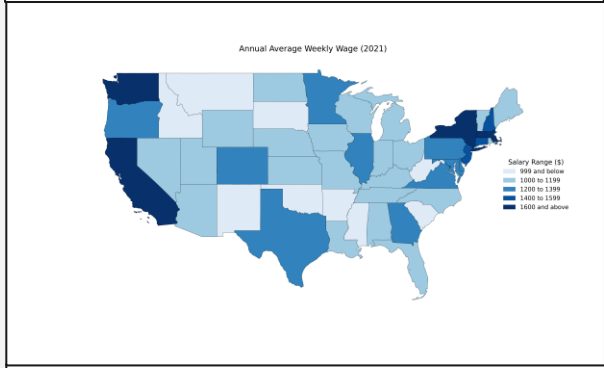
②

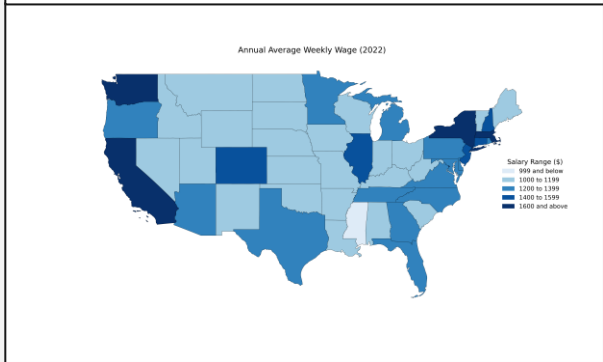
```
ax.set_yticks(y_positions + bar_width/2)
ax.set_yticklabels(states, fontsize = 10, rotation = 0)
ax.set_xlabel('Annual Average Weekly Wage ($)', fontsize = 12)
ax.set_title('Annual Average Weekly Wage for states and USA (2020 - 2021 - 2022)', fontsize = 16)

legend_labels = [
    f"2020 (USA Total: ${USA_data[0]:,.0f})",
    f"2021 (USA Total: ${USA_data[1]:,.0f})",
    f"2022 (USA Total: ${USA_data[2]:,.0f})"
]
legend_handles = [
    plt.Line2D([0], [0], color = colors[0], lw = 4),
    plt.Line2D([0], [0], color = colors[1], lw = 4),
    plt.Line2D([0], [0], color = colors[2], lw = 4)
]
ax.legend(legend_handles, legend_labels, title = 'Years', fontsize = 10, title_fontsize = 12)

plt.tight_layout()
plt.show()
```



Florida, **Idaho** and **Montana** are the three states with the highest growth in percentage of weekly salary from 2020 to 2022.







***Please note**: All three maps were made with the same code structure for the unemployment rate*

Consumer Price Index

```
Consumer_Price_Index = pd.read_excel('/content/file/Consumer_Price_Index.xlsx')
display(Consumer_Price_Index.head())
print('-------------------------')
print(Consumer_Price_Index.info())
print(Consumer_Price_Index.isnull().sum())
```

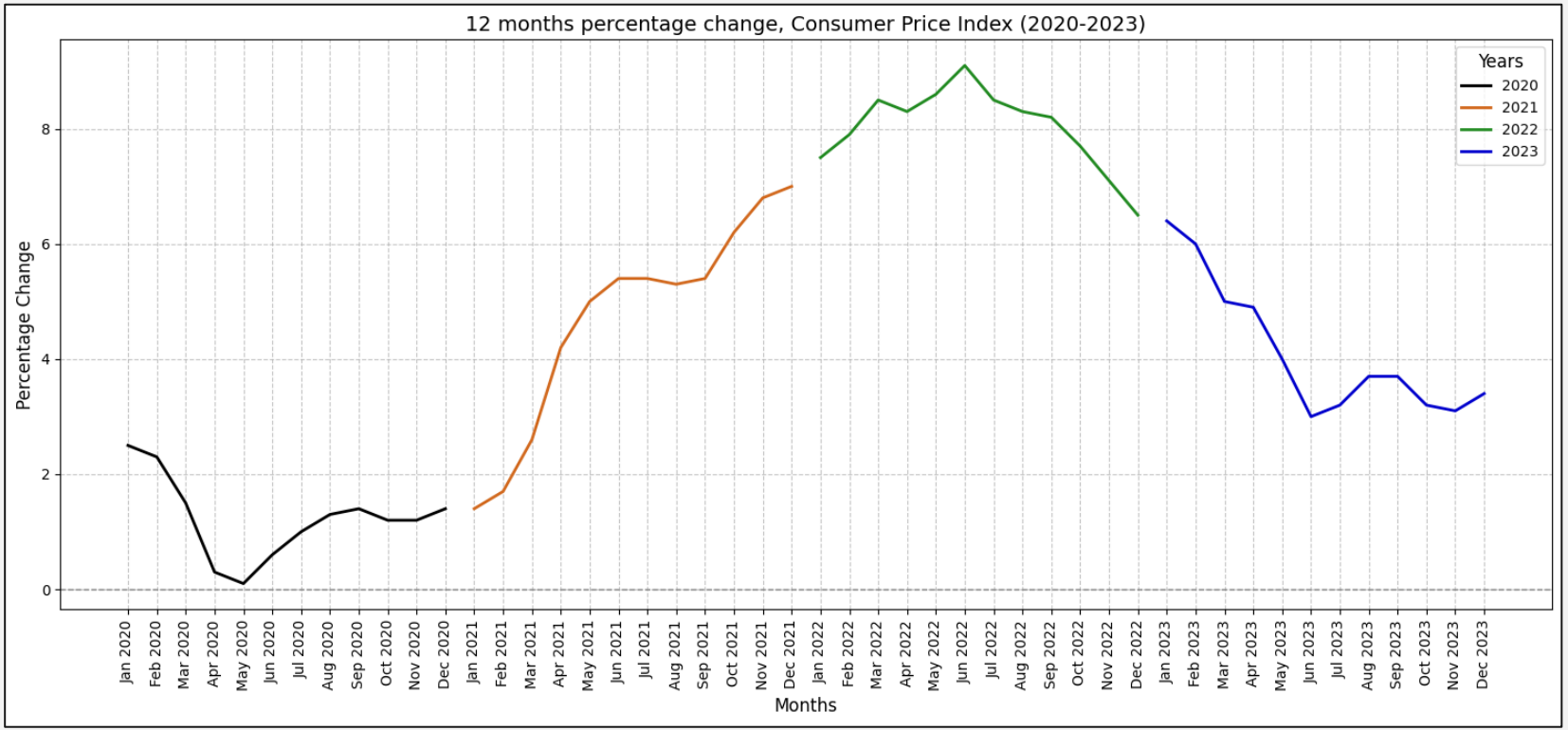
```
start_year = 2020
end_year = 2023
months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
month_year_sequence = [f'{month} {year}' for year in range(start_year, end_year + 1) for month in months]

Consumer_Price_Index['Month'] = month_year_sequence[:len(Consumer_Price_Index)]

Consumer_Price_Index.to_csv(f'/content/file/Consumer_Price_Index.csv', index = False)
display(Consumer_Price_Index)
```

Since there are so many categories regarding the consumer price index, we have only analyzed the first column: *'All items'*.

	Month	All items	Food	Food at home	Food away from home	Energy	Gasoline (all types)	Electricity	Natural gas (piped)	All items less food and energy	Commodities less food and energy commodities	Apparel	New vehicles	Medical care commodities	Services less energy services	Shelter	Medical care services	Education and communication
0	Jan 2020	2.5	1.8	0.7%	3.1%	6.2%	12.8%	0.5%	-3.2%	2.3%	-0.3%	-1.3%	0.1%	1.7%	3.1%	3.3%	5.1%	1.5%
1	Feb 2020	2.3%	1.8%	0.8%	3.0%	2.8%	5.6%	0.6%	-2.0%	2.4%	0.0%	-0.9%	0.4%	1.8%	3.1%	3.3%	5.3%	1.5%
2	Mar 2020	1.5%	1.9%	1.1%	3.0%	-5.7%	-10.2%	0.2%	-2.9%	2.1%	-0.2%	-1.6%	-0.4%	1.3%	2.8%	3.0%	5.5%	1.5%
3	Apr 2020	0.3%	3.5%	4.1%	2.8%	-17.7%	-32.0%	0.2%	-1.9%	1.4%	-0.9%	-5.7%	-0.6%	0.7%	2.2%	2.6%	5.8%	1.6%
4	May 2020	0.1%	4.0%	4.8%	2.9%	-18.9%	-33.8%	-0.2%	-0.3%	1.2%	-1.0%	-7.9%	-0.3%	0.8%	2.0%	2.5%	5.9%	1.6%
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
43	Aug 2023	3.7%	3.3%	3.0%	6.5%	-3.6%	-3.3%	2.1%	-16.5%	4.3%	0.2%	3.1%	2.9%	4.5%	5.9%	7.3%	-2.1%	1.0%
44	Sep 2023	3.7%	3.7%	2.4%	6.0%	-0.5%	3.0%	2.6%	-19.9%	4.1%	0.0%	2.3%	2.5%	4.2%	5.7%	7.2%	-2.6%	1.0%
45	Oct 2023	3.2%	3.3%	2.1%	5.4%	-4.5%	-5.3%	2.4%	-15.8%	4.0%	0.1%	2.6%	1.9%	4.7%	5.5%	6.7%	-2.0%	0.9%
46	Nov 2023	3.1%	2.9%	1.7%	5.3%	-5.4%	-8.9%	3.4%	-10.4%	4.0%	0.0%	1.1%	1.3%	5.0%	5.5%	6.5%	-0.9%	-0.1%
47	Dec 2023	3.4%	2.7%	1.3%	5.2%	-2.0%	-1.9%	3.3%	-13.8%	3.9%	0.2%	1.0%	1.0%	4.7%	5.3%	6.2%	-0.5%	-0.1%

```
data = Consumer_Price_Index

data['All items'] = data['All items'].replace({r'%': ''}, regex=True).astype(float)

months = ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec']
colors = {2020: 'black', 2021: 'chocolate', 2022: 'forestgreen', 2023: 'mediumblue'}

plt.figure(figsize = (15, 7))

for year in range(2020, 2024):
  all_months = [f'{month} {year}' for month in months]
  data_year = data[data['Month'].isin(all_months)]

  x_labels = all_months
  y_values = data_year['All items']

  plt.plot(x_labels, y_values, label = f'{year}', color = colors[year], linewidth = 2)

plt.title('12 months percentage change, Consumer Price Index (2020-2023)', fontsize = 14)
plt.xlabel('Months', fontsize = 12)
plt.ylabel('Percentage Change', fontsize = 12)
plt.xticks(rotation = 90, fontsize = 10)
plt.axhline(y = 0, color = 'grey', linestyle = '--', linewidth = 1)
plt.legend(title = 'Years', fontsize = 10, title_fontsize = 12)
plt.grid(visible = True, linestyle = '--', alpha = 0.7)

plt.tight_layout()
plt.show()
```

Consumer Price Index – All items



We took a look at the consumer price index for each month between 2020 and 2023 to see all the changes and how it has changed with the 2020 elections.

03

Voting behavior at geographic level

With a first hint of linear regression (chapter 5)

Voter turnout in the US – Data cleaning

Data cleaning process for the voter turnout dataset found from the US Census Bureau (2020).

```
input_file = ('/content/file/table04a.xlsx')
df = pd.read_excel(input_file)
display(df.head())
print('-------------------------')
print(df.info())
print(df.isnull().sum())
```

	Table with row headers in column A, and column headers in rows 5 through 6.	Unnamed: 1	Unnamed: 2	Unnamed: 3	Unnamed: 4	Unnamed: 5	Unnamed: 6	Unnamed: 7	Unnamed: 8	Unnamed: 9	Unnamed: 10	Unnamed: 11	Unnamed: 12
0	Table 4a. Reported Voting and Registration fo...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	(In thousands)	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	STATE	Total population	Total citizen population	Registered	NaN	NaN	NaN	NaN	Voted	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	Total registered	Percent registered\n(Total)	Margin of error 1	Percent registered\n(Citizen)	Margin of error 1	Total voted	Percent voted\n(Total)	Margin of error 1	Percent voted\n(Citizen)	Margin of error 1

```
-------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 64 entries, 0 to 63
Data columns (total 13 columns):
 #   Column                                                        Non-Null Count  Dtype 
---  ------                                                        --------------  ----- 
 0   Table with row headers in column A, and column headers in rows 5 through 6.  61 non-null    object
 1   Unnamed: 1                                                    53 non-null     object
 2   Unnamed: 2                                                    53 non-null     object
 3   Unnamed: 3                                                    54 non-null     object
 4   Unnamed: 4                                                    53 non-null     object
 5   Unnamed: 5                                                    53 non-null     object
 6   Unnamed: 6                                                    53 non-null     object
 7   Unnamed: 7                                                    53 non-null     object
 8   Unnamed: 8                                                    54 non-null     object
 9   Unnamed: 9                                                    53 non-null     object
 10  Unnamed: 10                                                   53 non-null     object
 11  Unnamed: 11                                                   53 non-null     object
 12  Unnamed: 12                                                   53 non-null     object
dtypes: object(13)
memory usage: 6.6+ KB
None
Table with row headers in column A, and column headers in rows 5 through 6.     3
Unnamed: 1                                                                     11
Unnamed: 2                                                                     11
Unnamed: 3                                                                     10
Unnamed: 4                                                                     11
Unnamed: 5                                                                     11
Unnamed: 6                                                                     11
Unnamed: 7                                                                     11
Unnamed: 8                                                                     10
Unnamed: 9                                                                     11
Unnamed: 10                                                                    11
Unnamed: 11                                                                    11
Unnamed: 12                                                                    11
dtype: int64
```

Voter turnout in the US – Data cleaning

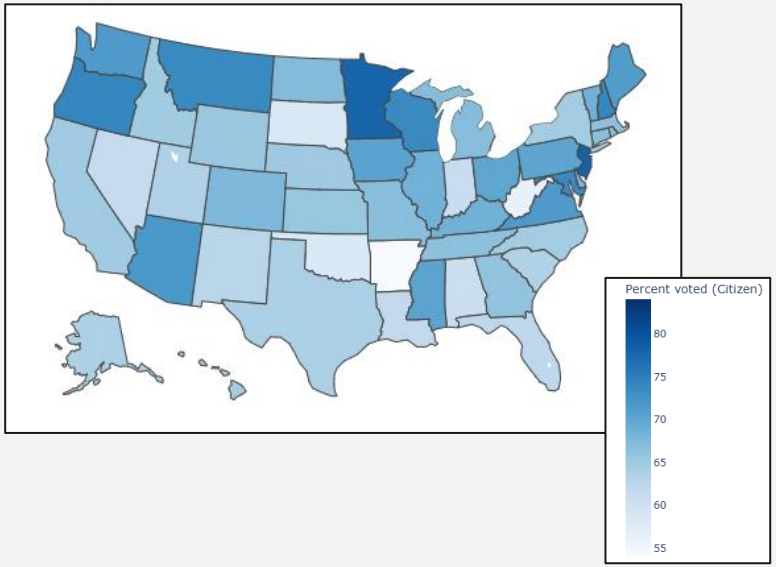
```
df = pd.read_excel(input_file, skiprows = 4)

original_header = df.columns.tolist()
first_row = df.iloc[0].tolist()

new_header = [col if pd.isna(val) else val for col, val in zip(original_header, first_row)]

df.columns = new_header
df = df[1:]

df.reset_index(drop=True, inplace=True)

df = df.dropna()

df.to_csv("cleaned_table04a.csv", index=False)

display(df)
```

In particular, the data contain information regarding the total citizens and total voted in each US States

	STATE	Total population	Total citizen population	Total registered	Percent registered\n(Total)	Margin of error 1	Percent registered\n(Citizen)	Margin of error 1	Total voted	Percent voted\n(Total)	Margin of error 1	Percent voted\n(Citizen)	Margin of error 1
0	UNITED STATES	252274.0	231593.0	168308	66.7	0.4	72.7	0.4	154628	61.3	0.4	66.8	0.4
1	ALABAMA	3769.0	3716.0	2527	67	3.1	68	3.1	2247	59.6	3.3	60.5	3.3
2	ALASKA	528.0	516.0	383	72.6	3.2	74.2	3.1	330	62.4	3.4	63.8	3.4
3	ARIZONA	5638.0	5075.0	3878	68.8	2.5	76.4	2.5	3649	64.7	2.6	71.9	2.6
4	ARKANSAS	2283.0	2195.0	1361	59.6	3.4	62	3.4	1186	51.9	3.4	54	3.5
...	...	...	...	...	...	...	...	...	...	...	...	...	...
47	VIRGINIA	6481.0	5974.0	4541	70.1	2.4	76	2.3	4275	66	2.5	71.5	2.4
48	WASHINGTON	5993.0	5389.0	4029	67.2	2.5	74.8	2.4	3854	64.3	2.6	71.5	2.5
49	WEST VIRGINIA	1397.0	1379.0	928	66.4	3.4	67.3	3.4	773	55.3	3.6	56.1	3.6
50	WISCONSIN	4538.0	4421.0	3391	74.7	2.7	76.7	2.6	3253	71.7	2.8	73.6	2.7
51	WYOMING	436.0	427.0	296	67.9	3.4	69.3	3.4	280	64.1	3.5	65.5	3.5

Voter turnout in the US – By state

```
affluence_df = pd.read_csv('cleaned_table04a.csv')

affluence_df.rename(columns={'STATE': 'State'}, inplace=True)
affluence_df['State'] = affluence_df['State'].str.title()

state_abbreviations = {
    'Alabama': 'AL', 'Alaska': 'AK', 'Arizona': 'AZ', 'Arkansas': 'AR', 'California': 'CA',
    'Colorado': 'CO', 'Connecticut': 'CT', 'Delaware': 'DE', 'Florida': 'FL', 'Georgia': 'GA',
    'Hawaii': 'HI', 'Idaho': 'ID', 'Illinois': 'IL', 'Indiana': 'IN', 'Iowa': 'IA', 'Kansas': 'KS',
    'Kentucky': 'KY', 'Louisiana': 'LA', 'Maine': 'ME', 'Maryland': 'MD', 'Massachusetts': 'MA',
    'Michigan': 'MI', 'Minnesota': 'MN', 'Mississippi': 'MS', 'Missouri': 'MO', 'Montana': 'MT',
    'Nebraska': 'NE', 'Nevada': 'NV', 'New Hampshire': 'NH', 'New Jersey': 'NJ', 'New Mexico': 'NM',
    'New York': 'NY', 'North Carolina': 'NC', 'North Dakota': 'ND', 'Ohio': 'OH', 'Oklahoma': 'OK',
    'Oregon': 'OR', 'Pennsylvania': 'PA', 'Rhode Island': 'RI', 'South Carolina': 'SC',
    'South Dakota': 'SD', 'Tennessee': 'TN', 'Texas': 'TX', 'Utah': 'UT', 'Vermont': 'VT',
    'Virginia': 'VA', 'Washington': 'WA', 'West Virginia': 'WV', 'Wisconsin': 'WI', 'Wyoming': 'WY'
}

affluence_df['State Abbreviation'] = affluence_df['State'].map(state_abbreviations)

fig = px.choropleth(
    affluence_df,
    locations='State Abbreviation',
    locationmode='USA-states',
    color='Percent voted\n(Citizen)',
    color_continuous_scale='Blues',
    scope='usa',
    title='Voter Turnout in the 2020 U.S. Elections - by State',
)

fig.show()
```



The map shows voter turnout by US states, in percentage.

Majority of the States registered greater than 60% of the population to the turnout.

Voter turnout in the US – Data cleaning

```
input_file = ('/content/file/table04b.xlsx')
df = pd.read_excel(input_file, skiprows=4)

original_header = df.columns.tolist()
first_row = df.iloc[0].tolist()

new_header = [col if pd.isna(val) else val for col, val in zip(original_header, first_row)]

df.columns = new_header
df = df[1:]

df.reset_index(drop=True, inplace=True)

df["STATE"] = df["STATE"].fillna(method='ffill')

df = df.dropna()

df.to_csv("cleaned_table04b.csv", index=False)

display(df)
```

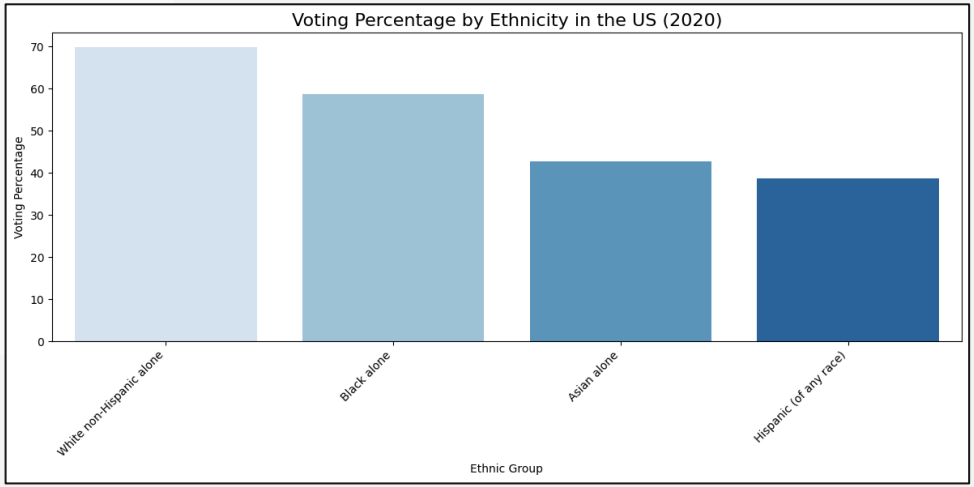
This dataset is similar to the previous one, analyzing voter turnout for each US state, except that this dataset also contains information regarding ethnic groups within each state.

	STATE	Sex, Race, and Hispanic-Origin	Total population	Total citizen population	Total registered	Percent registered\n(Total)	Margin of error 1	Percent registered\n(Citizen)	Margin of error 1	Total voted	Percent voted\n(Total)	Margin of error 1	Percent voted\n(Citizen)	Margin of error 1
0	US	Total	252274.0	231593	168308	66.7	0.4	72.7	0.4	154628	61.3	0.4	66.8	0.4
1	US	Male	121870.0	111485	79340	65.1	0.5	71.2	0.5	72474	59.5	0.5	65	0.5
2	US	Female	130404.0	120108	88968	68.2	0.5	74.1	0.5	82154	63	0.5	68.4	0.5
3	US	White alone	195227.0	181891	134889	69.1	0.4	74.2	0.4	124301	63.7	0.4	68.3	0.4
4	US	White non-Hispanic alone	157442.0	154827	118389	75.2	0.4	76.5	0.4	109830	69.8	0.4	70.9	0.4
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
567	WYOMING	Asian alone	2.0	-	-	B	B	B	B	-	B	B	B	B
568	WYOMING	Hispanic (of any race)	40.0	38	23	B	B	B	B	21	B	B	B	B
569	WYOMING	White alone or in combination	422.0	416	290	68.6	3.5	69.6	3.5	273	64.7	3.6	65.7	3.6
570	WYOMING	Black alone or in combination	4.0	3	3	B	B	B	B	3	B	B	B	B
571	WYOMING	Asian alone or in combination	4.0	2	2	B	B	B	B	2	B	B	B	B

Voter turnout in the US – By ethnicity

```
file_path = 'cleaned_table04b.csv'
data = pd.read_csv(file_path)

# Ensure numeric conversion for Total population and Total voted
data['Total population'] = pd.to_numeric(data['Total population'], errors='coerce').fillna(0).astype(int)
data['Total voted'] = pd.to_numeric(data['Total voted'], errors='coerce').fillna(0).astype(int)

us_data = data[data['STATE'] == 'US']
criteria = [
    'White non-Hispanic alone',
    'Black alone',
    'Asian alone',
    'Hispanic (of any race)'
]
us_data = us_data[us_data['Sex, Race, and Hispanic-Origin'].isin(criteria)]

ethnicity_data = us_data[['Sex, Race, and Hispanic-Origin', 'Total population', 'Total voted']]
ethnicity_data['Voting Percentage'] = (
    ethnicity_data['Total voted'] / ethnicity_data['Total population'] * 100
)

plt.figure(figsize=(12, 6))
sns.barplot(
    data=ethnicity_data,
    x='Sex, Race, and Hispanic-Origin',
    y='Voting Percentage',
    palette='Blues'
)
plt.title('Voting Percentage by Ethnicity in the US (2020)', fontsize=16)
plt.xticks(rotation=45, ha='right')
plt.ylabel('Voting Percentage')
plt.xlabel('Ethnic Group')

plt.tight_layout()
plt.show()
```

We selected the four ethnic groups that can represent the entire US population.



Linear regression – for choosing swing states

```
df = pd.read_excel('/content/file/REGRESSIONE.xlsx')
df = df.set_index('STATO')
display(df)
print('------------------------')
print(df.info())
```

STATO	% DEM 2020	Dem Historical Trend	% REP 2020	Rep Historical Trend	Avg Age	Avg Hourly Earnings ($)	Avg Unemployment Rate	% non-White
Alabama	0.3657	0	0.6203	1	39.6	30.53	0.065818	0.369
Alaska	0.4277	0	0.5283	1	35.9	37.26	0.084636	0.425
Arizona	0.4936	0	0.4906	0	38.8	33.40	0.079364	0.466
Arkansas	0.3478	0	0.6240	1	38.9	28.97	0.062909	0.315
California	0.6348	1	0.3432	0	37.8	40.24	0.103000	0.653
...	...	...	...	...	...	...	...	...
Virginia	0.5411	1	0.4400	0	38.9	34.58	0.066273	0.414
Washington	0.5797	1	0.3877	0	38.4	41.62	0.087000	0.362
West Virginia	0.2970	0	0.6863	1	42.9	29.31	0.084636	0.109
Wisconsin	0.4945	0	0.4882	0	40.4	33.64	0.066000	0.214
Wyoming	0.2655	0	0.6994	1	39.1	31.44	0.059000	0.186

51 rows × 8 columns

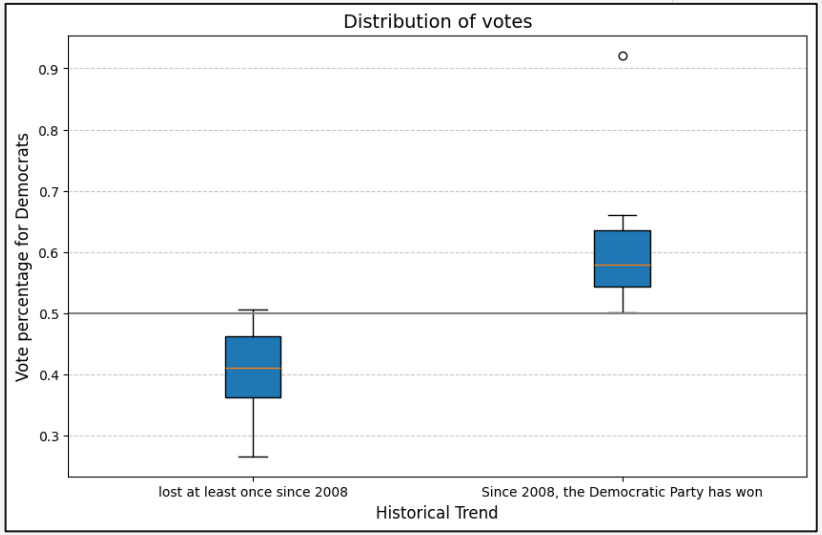
```
------------------------
<class 'pandas.core.frame.DataFrame'>
Index: 51 entries, Alabama to Wyoming
Data columns (total 8 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   % DEM 2020              51 non-null     float64
 1   Dem Historical Trend    51 non-null     int64
 2   % REP 2020              51 non-null     float64
 3   Rep Historical Trend    51 non-null     int64
 4   Avg Age                 51 non-null     float64
 5   Avg Hourly Earnings ($) 51 non-null     float64
 6   Avg Unemployment Rate   51 non-null     float64
 7   % non-White             51 non-null     float64
dtypes: float64(6), int64(2)
memory usage: 3.6+ KB
None
```

The following dataset shows for each state:

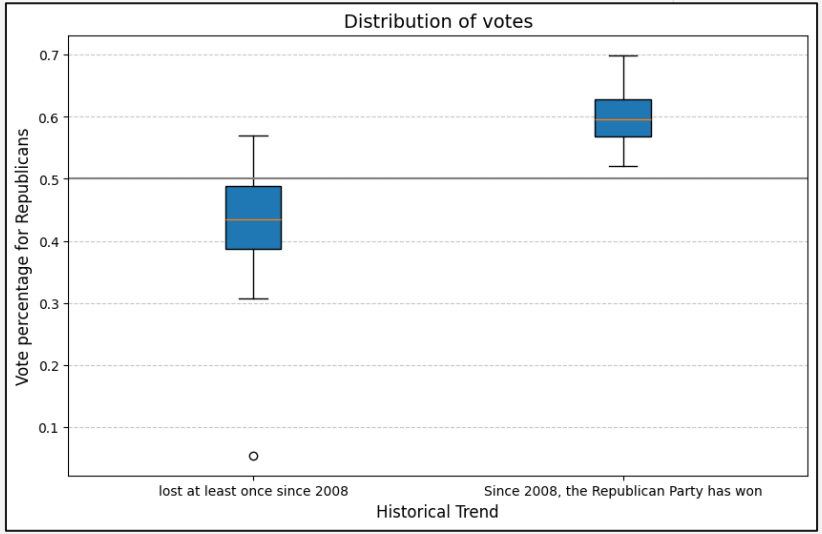
- **The percentage of non-white people**;
- **The unemployment rate**;
- **The average weekly earnings in dollars**;
- **The average age**;
- **A historical variable for both parties**;
- **The percentage of votes for both parties**.

Linear regression – for choosing swing states

```
grouped_data = df.groupby('Dem Historical Trend')['% DEM 2020'].apply(list)
plt.boxplot([grouped_data[0], grouped_data[1]],
            labels=["lost at least once since 2008", "Since 2008, the Democratic Party has won"],
            patch_artist=True)

plt.title("Distribution of votes", fontsize=14)
plt.xlabel("Historical Trend", fontsize=12)
plt.ylabel("Vote percentage for Democrats", fontsize=12)
plt.axhline(y = 0.5, color = 'grey')
plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.show()
```




```
grouped_data = df.groupby('Rep Historical Trend')['% REP 2020'].apply(list)
plt.boxplot([grouped_data[0], grouped_data[1]],
            labels=["lost at least once since 2008", "Since 2008, the Republican Party has won"],
            patch_artist=True)

plt.title("Distribution of votes", fontsize=14)
plt.xlabel("Historical Trend", fontsize=12)
plt.ylabel("Vote percentage for Republicans", fontsize=12)
plt.axhline(y = 0.5, color = 'grey')
plt.grid(axis='y', linestyle='--', alpha=0.7)

plt.show()
```



The historical variable takes the value of 1 if the reference party has always won in the state from 2008 to 2020 (4 consecutive elections), and 0 if at least once another party won.

Which are the swing states?

```
lst = df[(df['Dem Historical Trend'] == 0) &
         (df['Rep Historical Trend'] == 0) &
         ((df['% DEM 2020'].between(0.48, 0.52)) |
          (df['% REP 2020'].between(0.48, 0.52)))].index.tolist()

lst
```

```
['Arizona',
 'Florida',
 'Georgia',
 'Michigan',
 'North Carolina',
 'Pennsylvania',
 'Wisconsin']
```

We considered a swing state to be one where the percentage of votes are uncertain.

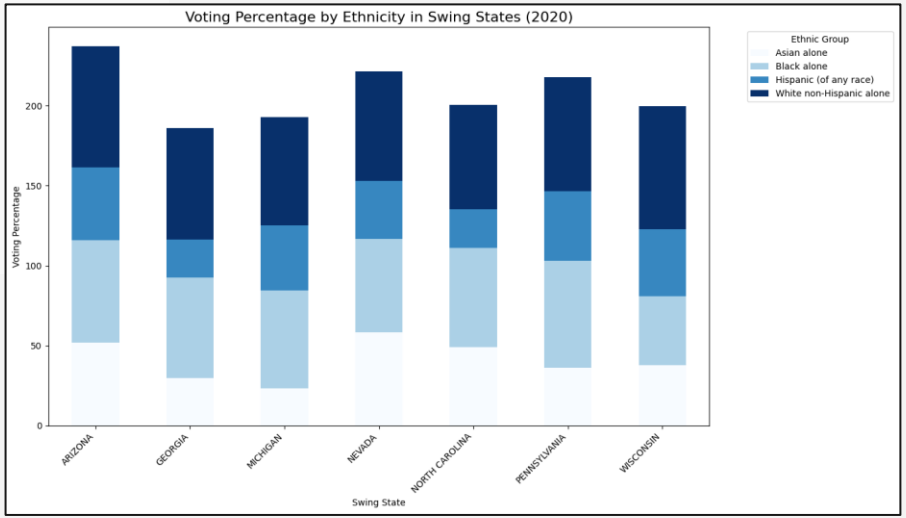
```
y = df['% DEM 2020']
X = df[['Dem Historical Trend']]
X = sm.add_constant(X)

fit = sm.OLS(y, X).fit()
print(fit.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             % DEM 2020   R-squared:                       0.614
Model:                            OLS   Adj. R-squared:                  0.606
Method:                 Least Squares   F-statistic:                     78.03
Date:                Tue, 21 Jan 2025   Prob (F-statistic):           1.04e-11
Time:                        10:16:27   Log-Likelihood:                 60.373
No. Observations:                  51   AIC:                            -116.7
Df Residuals:                      49   BIC:                            -112.9
Df Model:                           1
Covariance Type:            nonrobust
=========================================================================================
                            coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                     0.4082      0.014     29.585      0.000       0.380       0.436
Dem Historical Trend      0.1899      0.022      8.834      0.000       0.147       0.233
==============================================================================
Omnibus:                       27.801   Durbin-Watson:                   2.013
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               71.783
Skew:                           1.454   Prob(JB):                     2.59e-16
Kurtosis:                       8.032   Cond. No.                         2.46
==============================================================================

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

Turnout by ethnicity and swing states

```
# Continue from US-level ...
#
# -------------------------------------
# Step 2: Analyze data for swing states
swing_states = ['ARIZONA', 'GEORGIA', 'MICHIGAN', 'NORTH CAROLINA', 'NEVADA', 'PENNSYLVANIA', 'WISCONSIN']
data_swing_states = data[data['STATE'].isin(swing_states)]

swing_ethnicity_data = data_swing_states[
    ['STATE', 'Sex, Race, and Hispanic-Origin', 'Total population', 'Total voted']
]
swing_ethnicity_data = swing_ethnicity_data[swing_ethnicity_data['Sex, Race, and Hispanic-Origin'].isin(criteria)]
swing_ethnicity_data['Voting Percentage'] = (
    swing_ethnicity_data['Total voted'] / swing_ethnicity_data['Total population'] * 100
)

swing_ethnicity_data['Voting Percentage'] = pd.to_numeric(swing_ethnicity_data['Voting Percentage'], errors='coerce')

stacked_data = swing_ethnicity_data.pivot(
    index='STATE',
    columns='Sex, Race, and Hispanic-Origin',
    values='Voting Percentage'
)

stacked_data.plot(kind='bar', stacked=True, figsize=(14, 8), cmap='Blues')
plt.title('Voting Percentage by Ethnicity in Swing States (2020)', fontsize=16)
plt.xticks(rotation=45, ha='right')
plt.ylabel('Voting Percentage')
plt.xlabel('Swing State')
plt.legend(title='Ethnic Group', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```

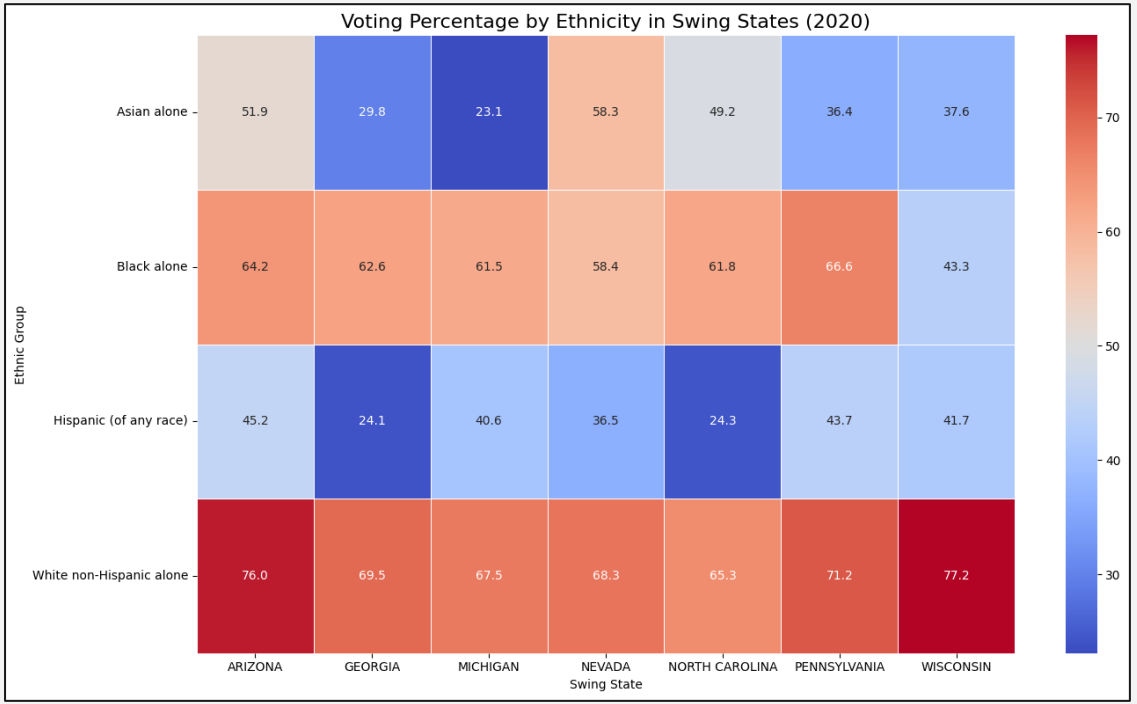
After the selection of the most interesting States, we firstly calculated the affluences of various ethnicities at the turnout.



Turnout by ethnicity and swing states

```
# As alternative, an heatmap of the swing states turnout by ethnicites
#
# -------------------------------------
# Heatmap visualization
heatmap_data = swing_ethnicity_data.pivot(
    index='Sex, Race, and Hispanic-Origin',
    columns='STATE',
    values='Voting Percentage'
)

plt.figure(figsize=(14, 8))
sns.heatmap(
    heatmap_data,
    annot=True,
    fmt='.1f',
    cmap='coolwarm',
    linewidths=0.5
)
plt.title('Voting Percentage by Ethnicity in Swing States (2020)',
          fontsize=16)
plt.xlabel('Swing State')
plt.ylabel('Ethnic Group')
plt.tight_layout()
plt.show()
```

```
# -------------------------------------
swing_ethnicity_data.to_csv('swing_states_ethnicity_analysis.csv', index=False)
```



Voting preferences by ethnicities and swing states

①

```python
original_csv_path = "swing_states_ethnicity_analysis.csv"
aggregated_csv_path = "/content/file/aggregated_voting_percentages.csv"

original_data = pd.read_csv(original_csv_path)
aggregated_data = pd.read_csv(aggregated_csv_path)

original_data.loc[
    original_data['Sex, Race, and Hispanic-Origin'] == 'White non-Hispanic alone',
    ['Biden (%)', 'Trump (%)', 'Other (%)']
] = aggregated_data.loc[aggregated_data['Sex, Race, and Hispanic-Origin'] == 'White', ['Biden (%)', 'Trump (%)', 'Other (%)']].values

non_white_categories = ['Black alone', 'Asian alone', 'Hispanic (of any race)']
for category in non_white_categories:
    original_data.loc[
        original_data['Sex, Race, and Hispanic-Origin'] == category,
        ['Biden (%)', 'Trump (%)', 'Other (%)']
    ] = aggregated_data.loc[aggregated_data['Sex, Race, and Hispanic-Origin'] == 'Non-White', ['Biden (%)', 'Trump (%)', 'Other (%)']].values

final_csv_path = "updated_merged_swing_states_ethnicity_analysis.csv"
original_data.to_csv(final_csv_path, index=False)
```

Starting from merging two different dataset (1): US Census Bureau and AP News.

②

```python
file_path = 'updated_merged_swing_states_ethnicity_analysis.csv'
data = pd.read_csv(file_path)

non_white_categories = [
    "Black alone",
    "Asian alone",
    "Hispanic (of any race)"
]

data['Non-white'] = data['Sex, Race, and Hispanic-Origin'].apply(
    lambda x: "Non-white" if x in non_white_categories else "White"
)

# ATTENTION: the following is an hypothetic scenario, based on the own datasets
# Modify percentages to be proportionate to each ethnicity's total population within each state

data['Biden votes'] = 0
data['Trump votes'] = 0
data['Other votes'] = 0

def calculate_votes(group):
    for index, row in group.iterrows():
        biden_votes = (row['Total voted'] * row['Biden (%)']) / 100
        trump_votes = (row['Total voted'] * row['Trump (%)']) / 100
        other_votes = (row['Total voted'] * row['Other (%)']) / 100

        group.at[index, 'Biden votes'] = biden_votes
        group.at[index, 'Trump votes'] = trump_votes
        group.at[index, 'Other votes'] = other_votes

    return group

data = data.groupby(['STATE']).apply(calculate_votes)
```

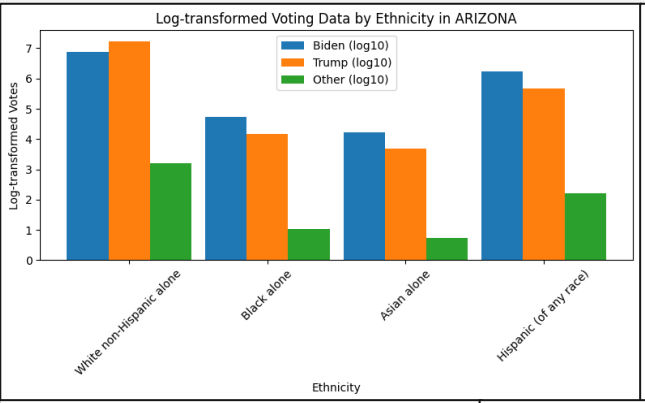
③

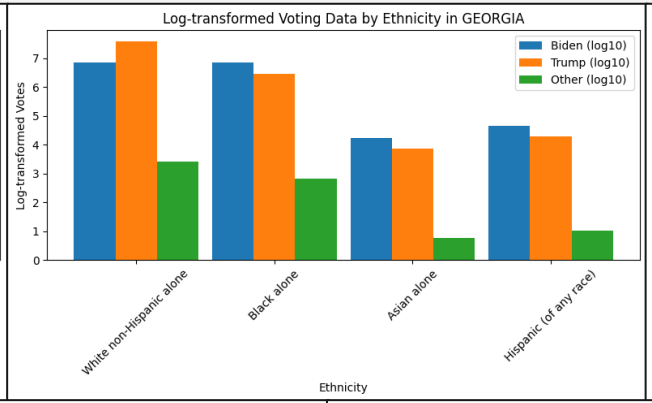
```python
# Visualize the updated data in a log scale
states = data['STATE'].unique()
for state in states:
    state_data = data[data['STATE'] == state]
    plt.figure(figsize=(8, 5))

    x = range(len(state_data))

    # Logaritmic transformation
    biden_votes_log = np.log1p(state_data['Biden votes'])
    trump_votes_log = np.log1p(state_data['Trump votes'])
    other_votes_log = np.log1p(state_data['Other votes'])

    plt.bar(x, biden_votes_log, width=0.3, label='Biden (log10)', align='center')
    plt.bar([p + 0.3 for p in x], trump_votes_log, width=0.3, label='Trump (log10)', align='center')
    plt.bar([p + 0.6 for p in x], other_votes_log, width=0.3, label='Other (log10)', align='center')

    plt.title(f'Log-transformed Voting Data by Ethnicity in {state}')
    plt.xlabel('Ethnicity')
    plt.ylabel('Log-transformed Votes')
    plt.xticks([p + 0.3 for p in x], state_data['Sex, Race, and Hispanic-Origin'], rotation=45)
    plt.legend()
    plt.tight_layout()
    plt.show()
```

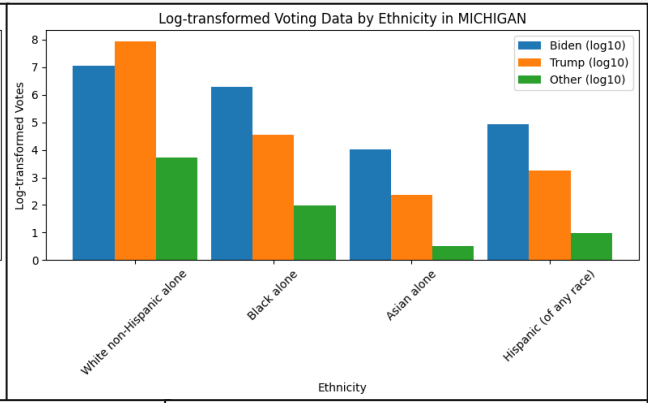
Up to computing the Candidate votes based on the voting population of each swing state (2 - 3).

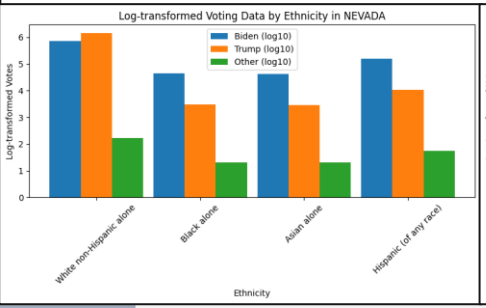
Then we extracted the voting preferences of various ethnicities from the various swing states.

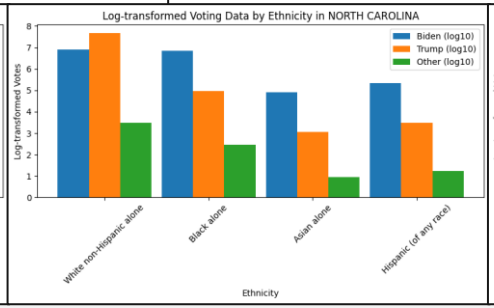
Voting preferences by ethnicities and swing states

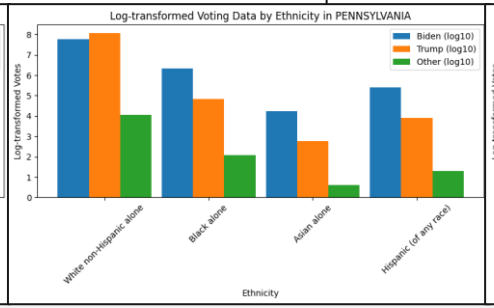


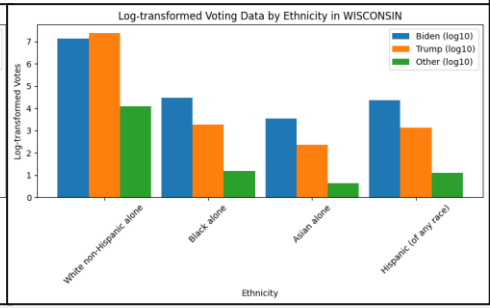












Please note: *Results are presented on the log-scale for a better vision*

04

Electoral topics

Abortion
Mexico wall
Gun Laws
Climate change
Import taxes

Social main topics– Data cleaning

```
file_path='/content/file/MainThemeData.xlsx'
df = pd.read_excel(file_path)

display(df)
```

	State	Division	Abortion legal	Abortion illegal	US-Mexico Wall pro	US-Mexico Wall against	Gun laws more strict	Gun laws no more strict	Climate change concerned	Climate change no concerced	import tax favor	import tax oppose
0	National	White	0.57	0.43	0.54	0.46	0.48	0.52	0.65	0.35	0.62	0.38
1	National	Non-white	0.67	0.33	0.32	0.68	0.68	0.32	0.77	0.23	0.53	0.47
2	National	Men	0.57	0.43	0.54	0.42	0.47	0.52	0.65	0.35	0.61	0.39
3	National	Women	0.61	0.39	0.44	0.54	0.59	0.48	0.75	0.25	0.59	0.41
4	National	No college	0.56	0.44	0.53	0.47	0.48	0.52	0.67	0.33	0.62	0.38
...	...	...	...	...	...	...	...	...	...	...	...	...
75	Wisconsin	College	0.59	0.41	0.42	0.58	0.62	0.38	0.71	0.29	0.59	0.41
76	Wisconsin	under 45	0.62	0.38	0.36	0.64	0.54	0.46	0.69	0.31	0.53	0.47
77	Wisconsin	over 45	0.53	0.47	0.49	0.51	0.49	0.51	0.64	0.36	0.68	0.32
78	Wisconsin	Biden voter	0.83	0.17	0.08	0.92	0.84	0.16	0.94	0.06	0.52	0.48
79	Wisconsin	Trump voter	0.28	0.72	0.88	0.12	0.22	0.78	0.42	0.58	0.75	0.25

80 rows × 12 columns

```
------------------------
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 80 entries, 0 to 79
Data columns (total 12 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   State                       80 non-null     object
 1   Division                    80 non-null     object
 2   Abortion legal              79 non-null     float64
 3   Abortion illegal            79 non-null     float64
 4   US-Mexico Wall pro          79 non-null     float64
 5   US-Mexico Wall against      79 non-null     float64
 6   Gun laws more strict        79 non-null     float64
 7   Gun laws no more strict     79 non-null     float64
 8   Climate change concerned    79 non-null     float64
 9   Climate change no concerced 79 non-null     float64
 10  import tax favor            79 non-null     float64
 11  import tax oppose           79 non-null     float64
dtypes: float64(10), object(2)
memory usage: 7.6+ KB
None
State                       0
Division                    0
Abortion legal              1
Abortion illegal            1
US-Mexico Wall pro          1
US-Mexico Wall against      1
Gun laws more strict        1
Gun laws no more strict     1
Climate change concerned    1
Climate change no concerced 1
import tax favor            1
import tax oppose           1
dtype: int64
```

This dataset from AP news contains information regarding the social topics that were most discussed during the 2020 elections: the most relevant ones that were a key point for winning the elections.

Social main topics– Data cleaning

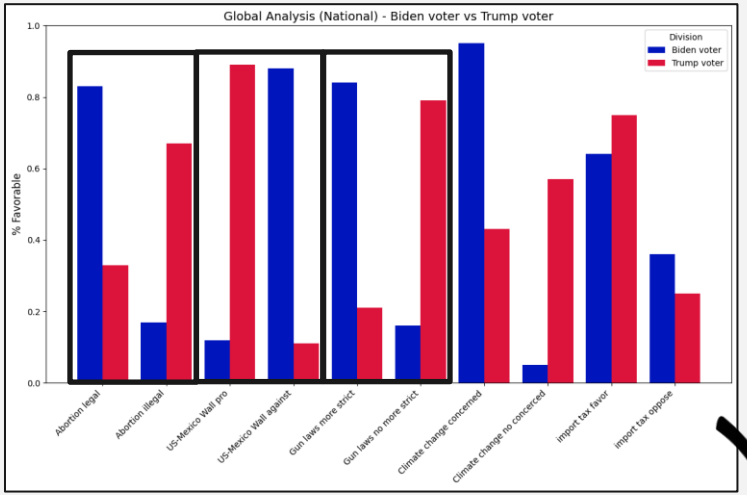
①
```python
def save_and_show_plot(title, ax):
    ax.set_title(title, fontsize=14)
    ax.set_xlabel('')
    ax.set_ylabel('% Favorable', fontsize=12)
    ax.set_ylim(0, 1)
    plt.xticks(rotation=45, ha='right')
    plt.tight_layout()
    plt.show()

def plot_bars(ax, x, width, data, categories, colors, label_key):
    for i, category in enumerate(categories):
        subset = data[data[label_key] == category]
        ax.bar([pos + i * width for pos in x], subset['Percentage'],
               width=width, label=category, color=colors[i])

def generic_analysis(data, x_labels, title, categories, colors, label_key):
    fig, ax = plt.subplots(figsize=(12, 8))
    x = range(len(x_labels))
    width = 0.8 / len(categories)
    if colors is None:
        colors = plt.cm.tab10.colors[:len(categories)]
    plot_bars(ax, x, width, data, categories, colors, label_key)
    ax.set_xticks([pos + width * (len(categories) - 1) / 2 for pos in x])
    ax.set_xticklabels(x_labels)
    ax.legend(title=label_key)
    save_and_show_plot(title, ax)
```

②
```python
pair_colors = {
    ('White', 'Non-white'): ('#1f77b4', '#aec7e8'),
    ('Men', 'Women'): ('#ff7f0e', '#ffbb78'),
    ('No college', 'College'): ('#2ca02c', '#98df8a'),
    ('under 45', 'over 45'): ('#d62728', '#ff9896'),
    ('Biden voter', 'Trump voter'): ('#0015BC', '#DC143C')
}

colors = {
    'White': '#1f77b4',
    'Non-white': '#aec7e8',
    'Men': '#ff7f0e',
    'Women': '#ffbb78',
    'No college': '#2ca02c',
    'College': '#98df8a',
    'under 45': '#d62728',
    'over 45': '#ff9896',
    'Biden voter': '#0015BC',
    'Trump voter': '#DC143C'
}
pairs = [
        ('White', 'Non-white'),
        ('Men', 'Women'),
        ('No college', 'College'),
        ('under 45', 'over 45'),
        ('Biden voter', 'Trump voter')
]
```

Data preparation and definitions of some frequently used function.

Social main topics– National analysis

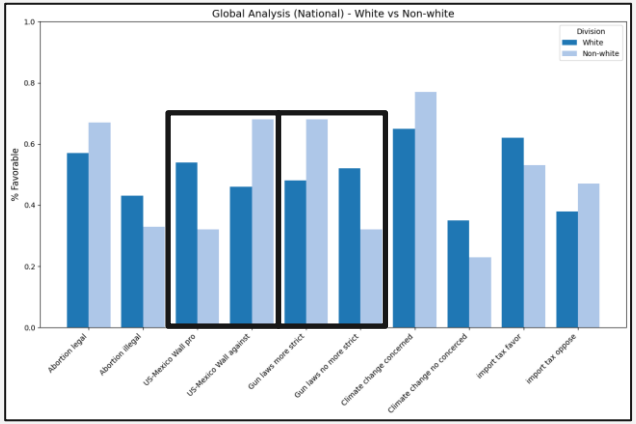
```
national_data = df[df['State'] == 'National']

def global_analysis_by_pairs():
    for pair in pairs:
        pair_data = national_data[national_data['Division'].isin(pair)]
        melted_data = pair_data.melt(id_vars=['State', 'Division'],
                                     var_name='Theme',
                                     value_name='Percentage')
        themes = melted_data['Theme'].unique()
        colors = pair_colors.get(pair)
        generic_analysis(melted_data, themes,
                         f'Global Analysis (National) - {pair[0]} vs {pair[1]}',
                         pair, colors, 'Division')
global_analysis_by_pairs()
```

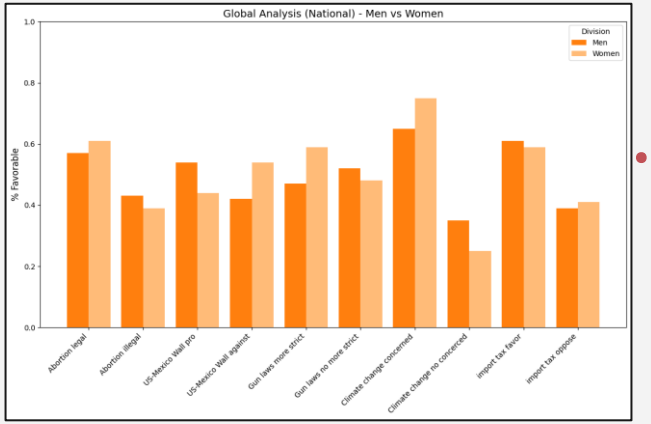


At the national level, it immediately becomes clear how supporters of various parties are extremely divided on different issues. Specifically, this applies to topics such as abortion, the Mexican border wall and gun restrictions.

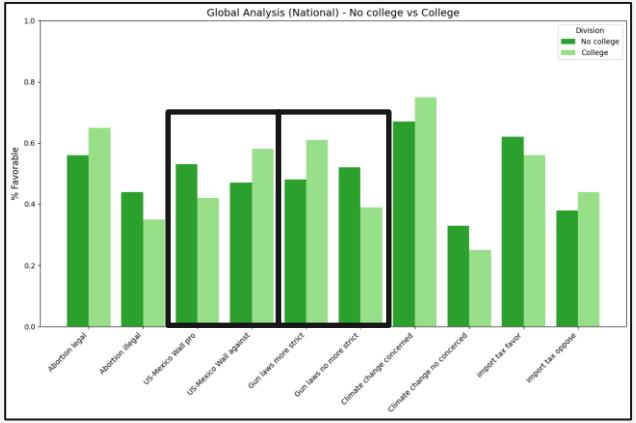
Due to concerns about climate change, we notice that those who voted for Biden are extremely worried, whereas Trump voters are split 50 – 50 on the issue.

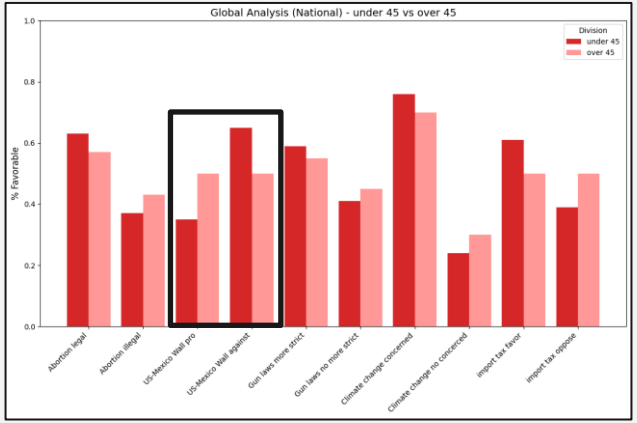
Social main topics– National analysis





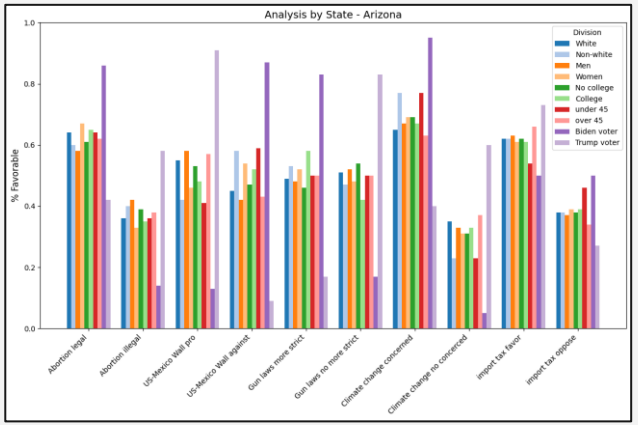
No significant differences between men and women. Women seem slightly more inclined toward Democratic positions.

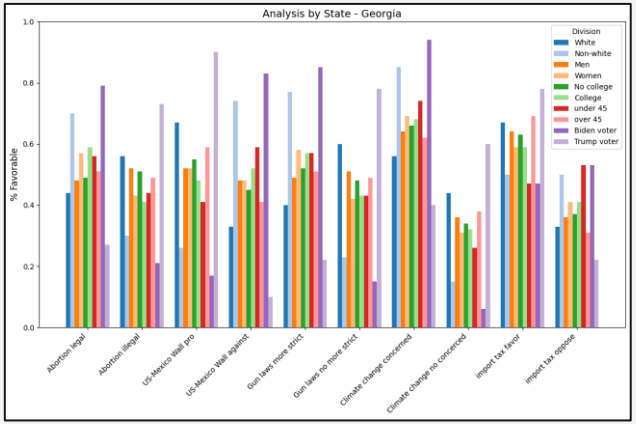


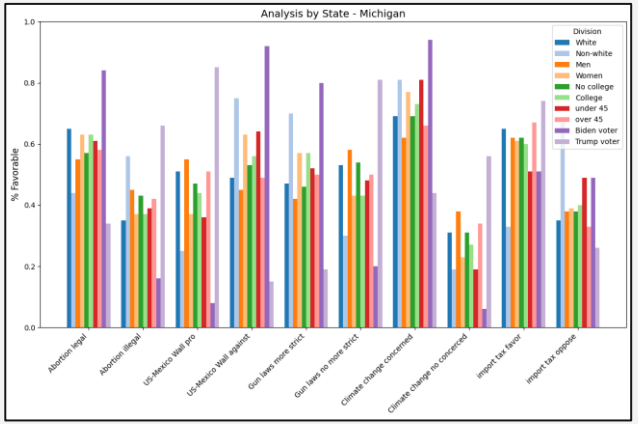


Social main topics– Analysis by state

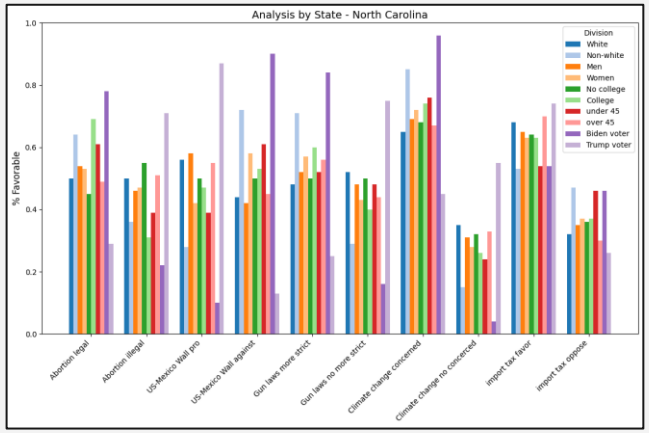
```
def state_analysis():
    states = df['State'].unique()
    for state in states:
        if state != 'National':
            state_data = df[df['State'] == state]
            melted_data = state_data.melt(id_vars=['State', 'Division'],
                                          var_name='Theme',
                                          value_name='Percentage')
            themes = melted_data['Theme'].unique()
            divisions = melted_data['Division'].unique()
            colors = plt.cm.tab20.colors[:len(divisions)]
            generic_analysis(melted_data, themes,
                             f'Analysis by State - {state}',
                             divisions, colors, 'Division')
state_analysis()
```

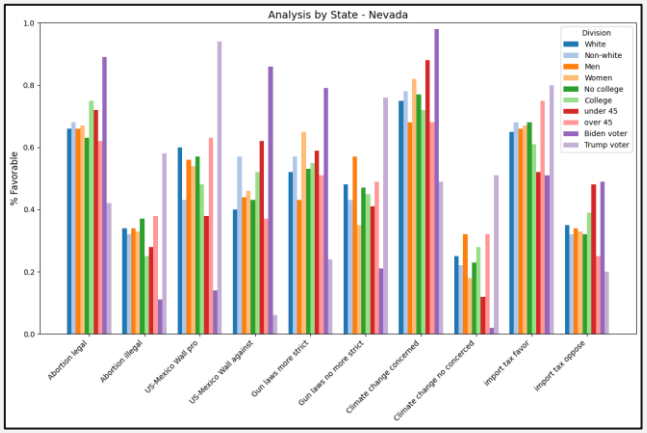


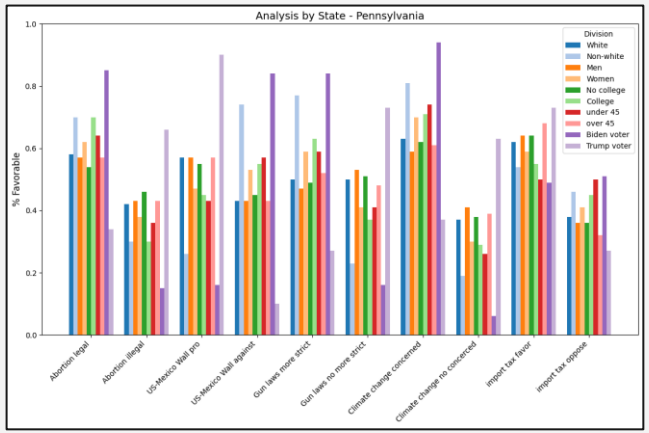


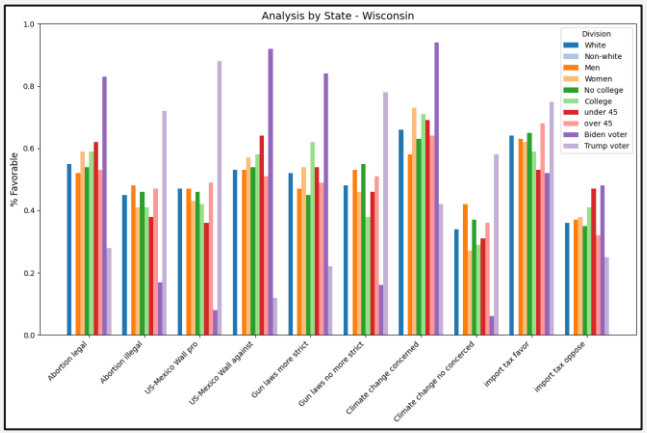


Social main topics– Analysis by state







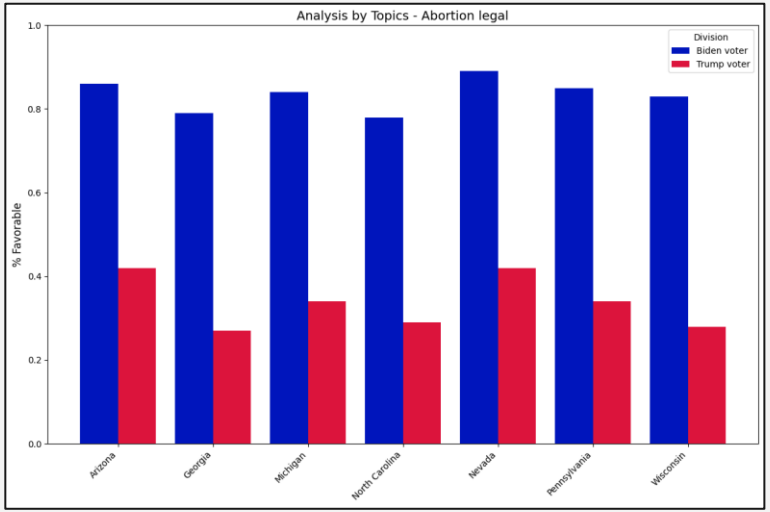


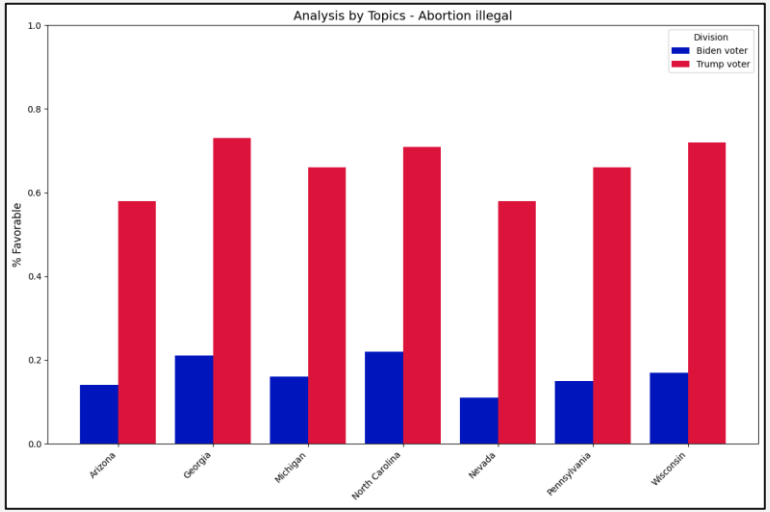
Analysis by topics - Abortion

```
df_without_national = df[df['State'] != 'National']
swing_states_list=list(df_without_national['State'].unique())
def topics_analysis():
    topics = [col for col in df.columns if col not in ['State', 'Division']]
    for topic in topics:
        for pair in pairs:
            pair_data = df[(df['Division'].isin(pair)) &
             (df['State'] != 'National')].copy()
            pair_data.rename(columns={topic: 'Percentage'}, inplace=True)
            colors = pair_colors.get(pair)
            generic_analysis(pair_data, swing_states_list,
                             f'Analysis by Topics - {topic}',
                             pair, colors, 'Division')
topics_analysis()
```

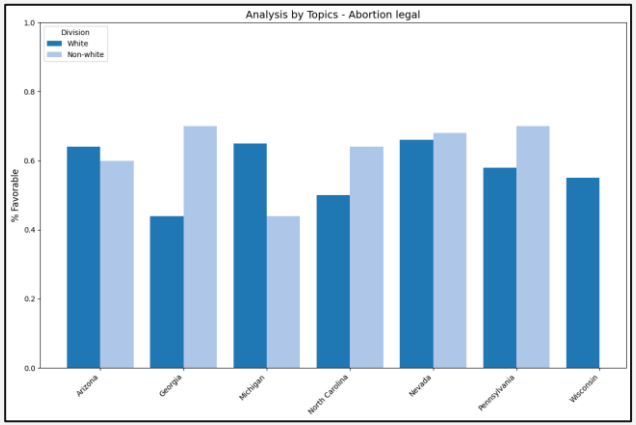
Differences between swing states.

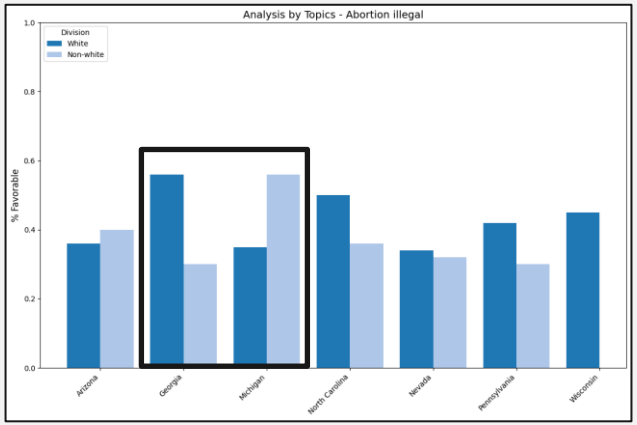
We can observe a significant divergence on the topic of abortion across all swing states.

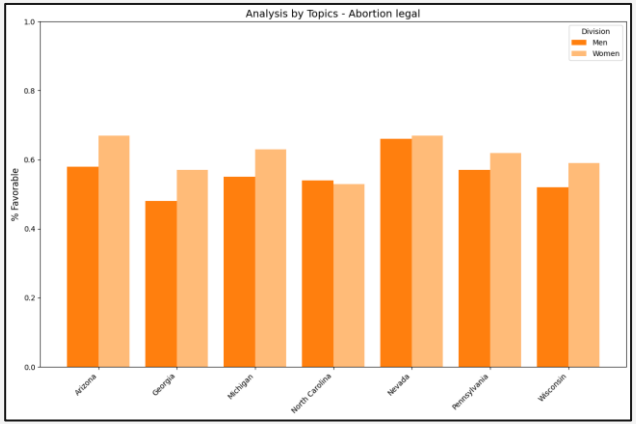


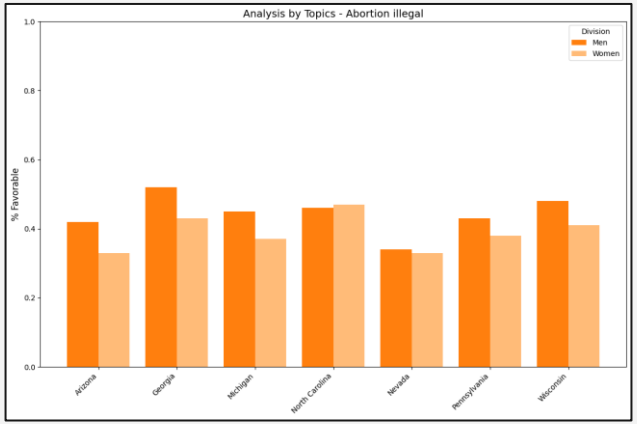


Analysis by topics - Abortion

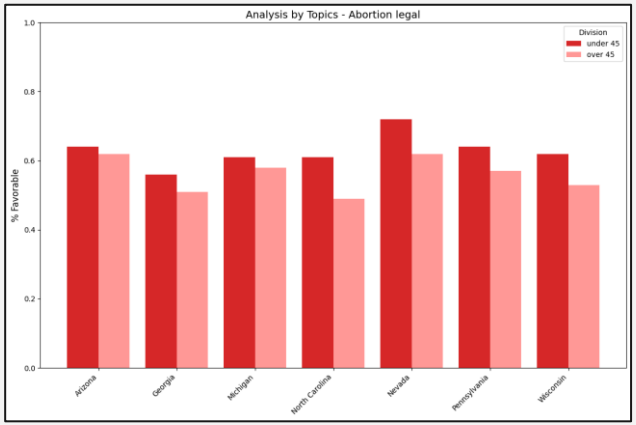


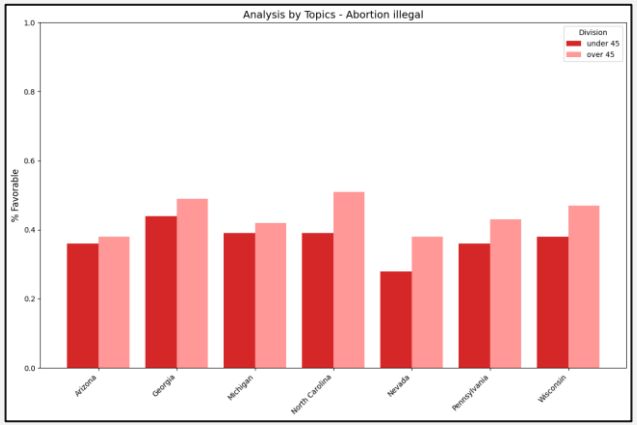


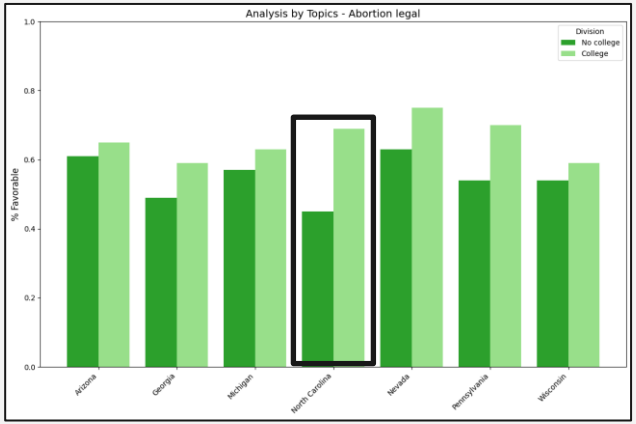


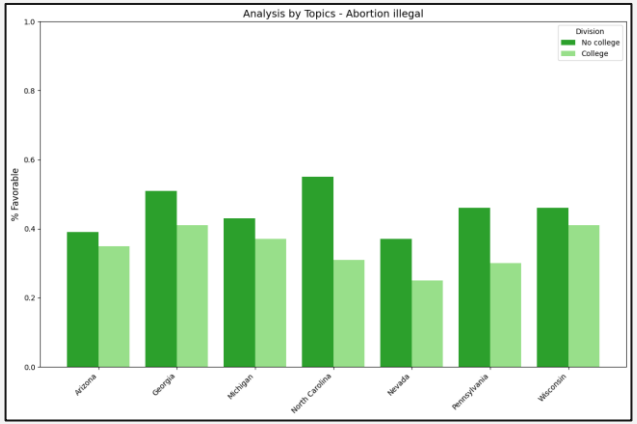


Analysis by topics - Abortion

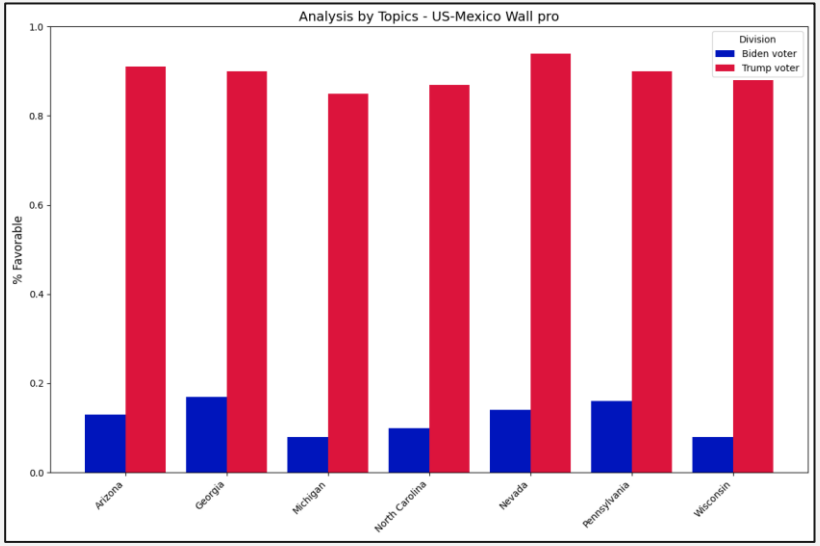


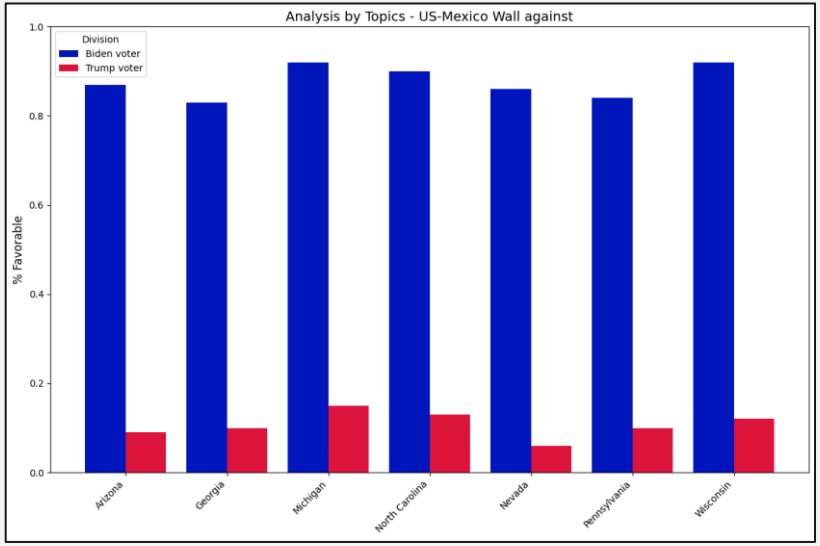






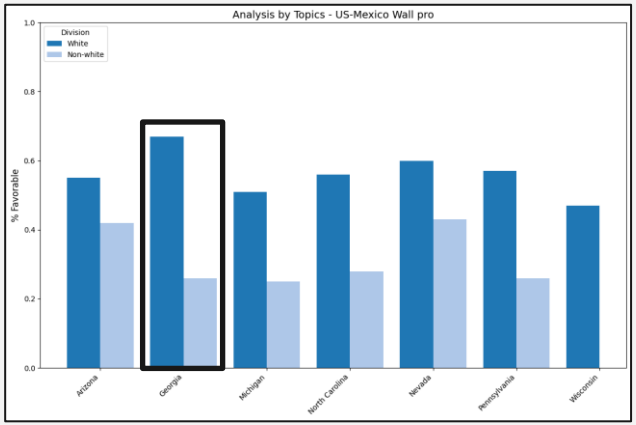
Analysis by topics – Mexico Wall

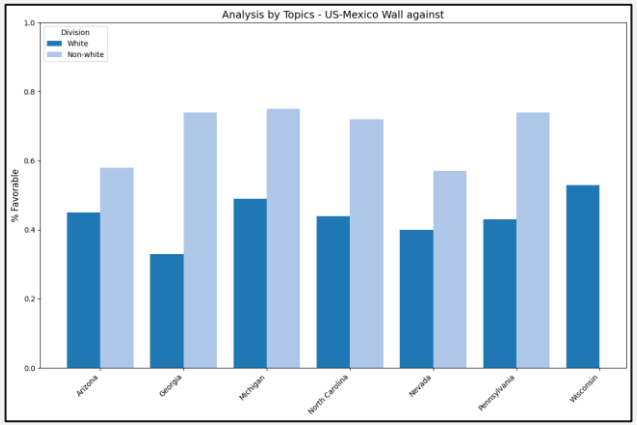


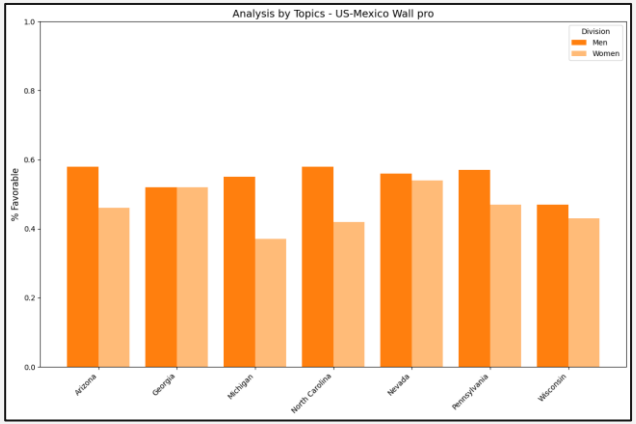


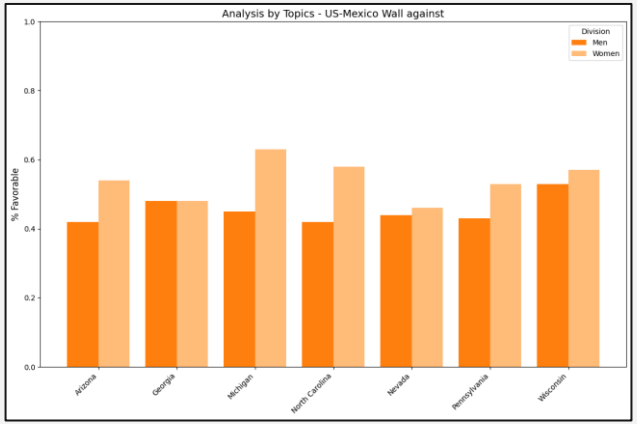
We can observe a significant divergence on the topic of the Mexico Wall across all swing states.

Analysis by topics – Mexico Wall

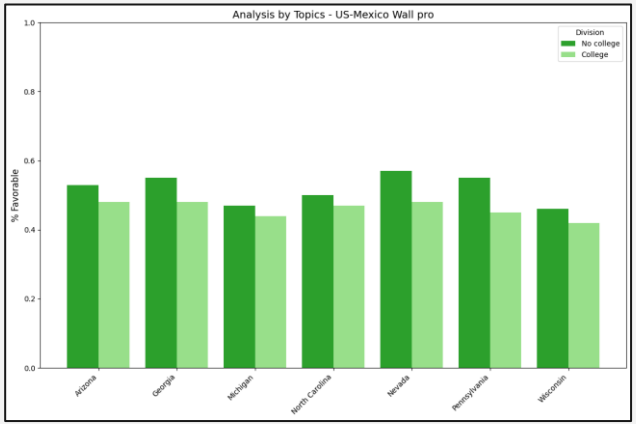


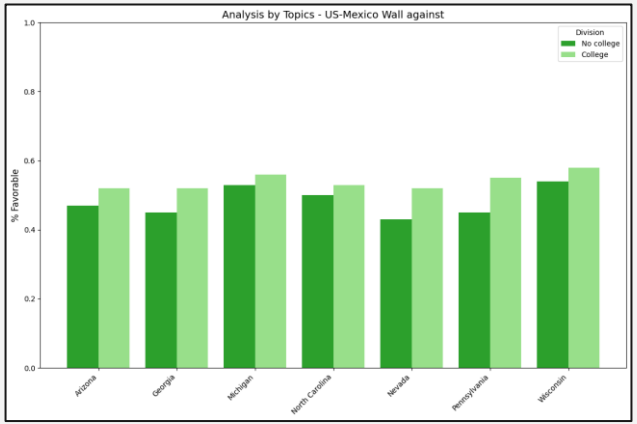


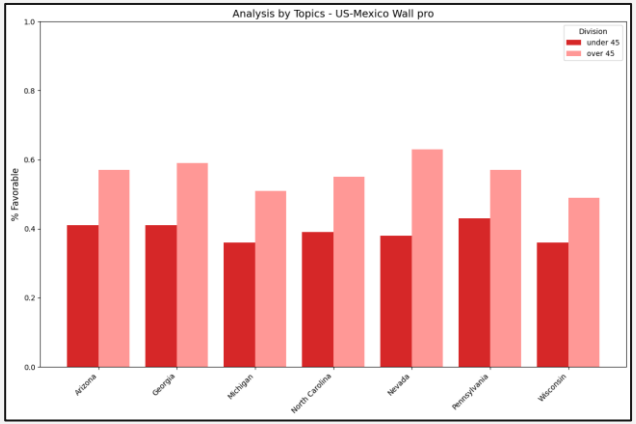


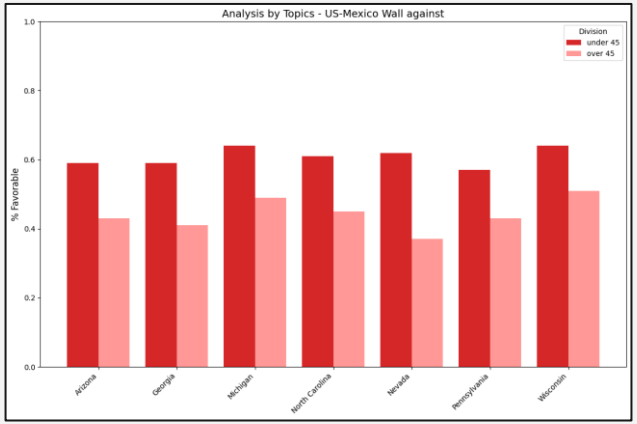


Analysis by topics – Mexico Wall

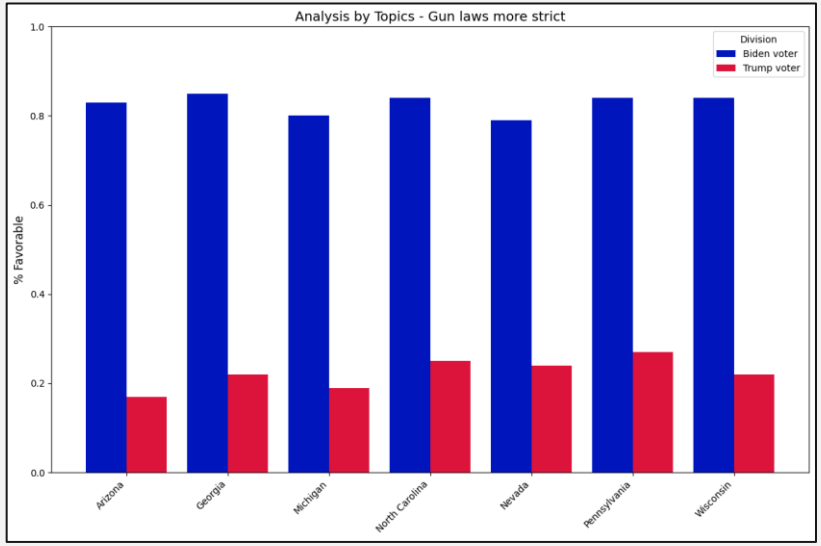


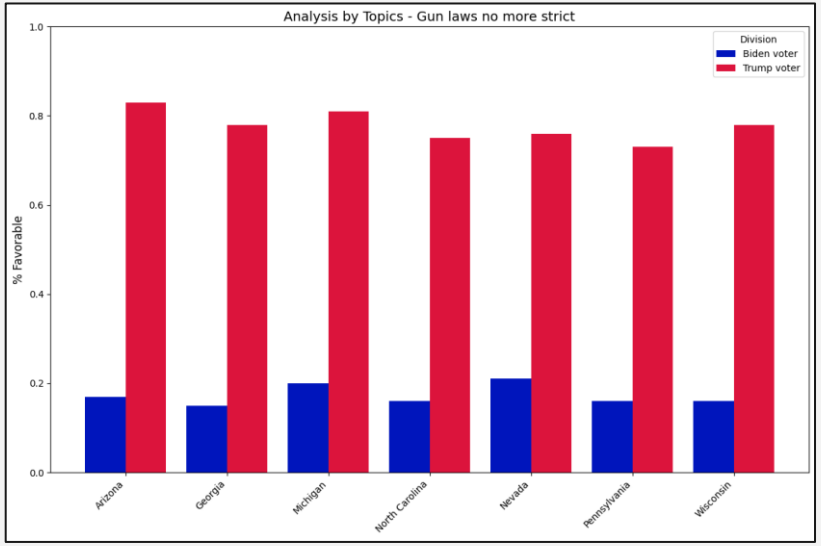






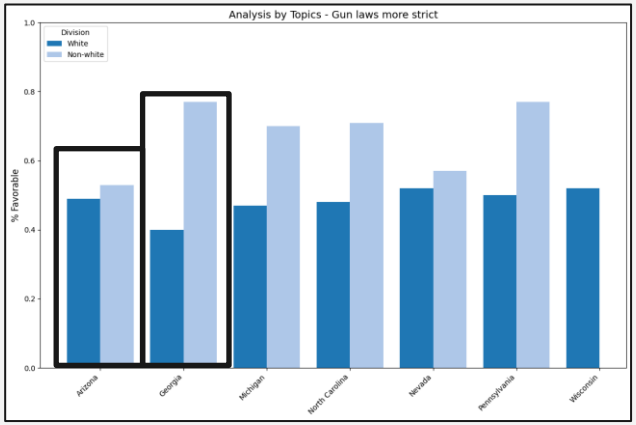
Analysis by topics – Gun Laws

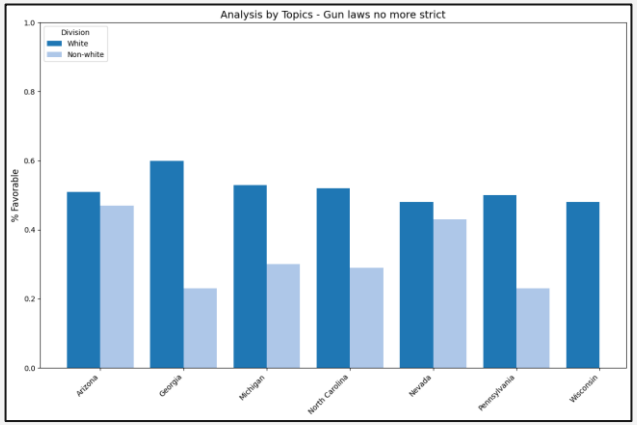


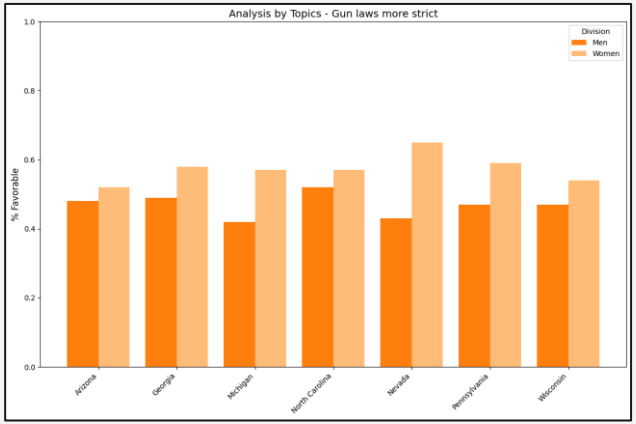


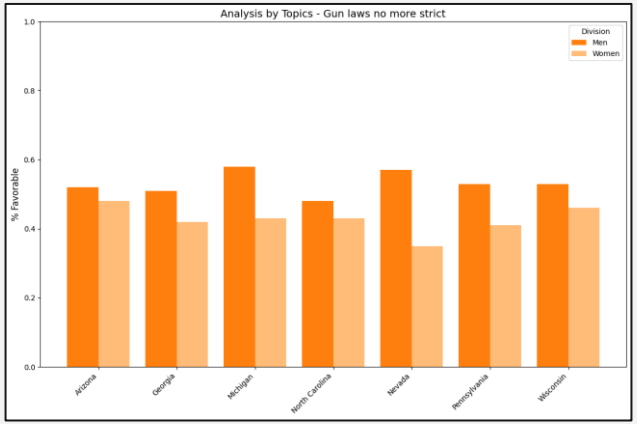
Trump voters believe that gun laws should not be more restrictive, while Biden voters hold the opposite view.

Analysis by topics – Gun Laws

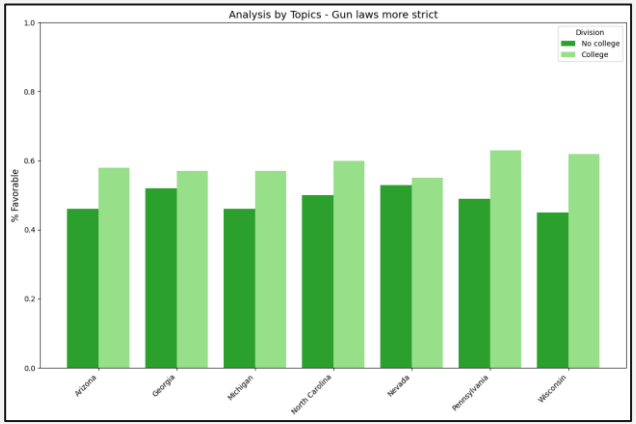


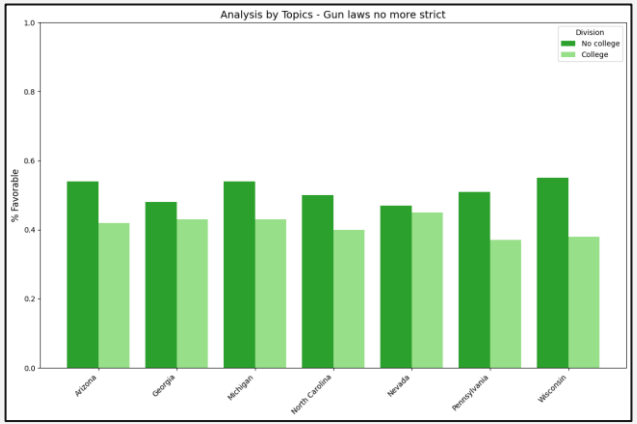


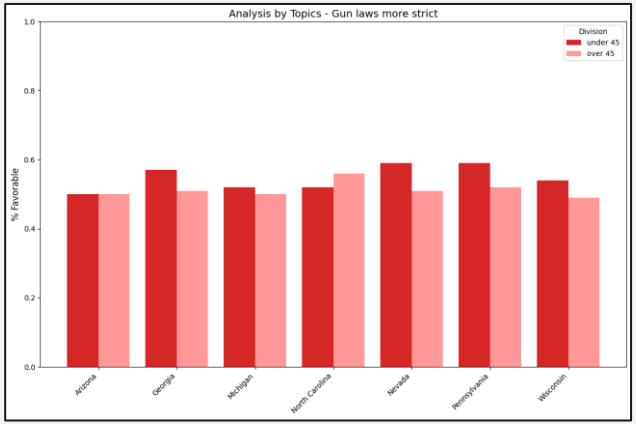


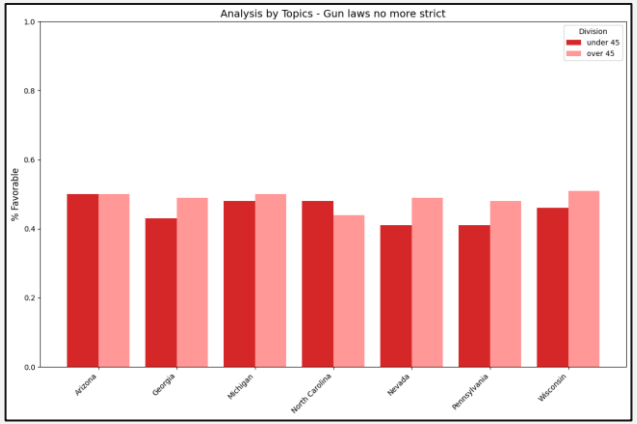


Analysis by topics – Gun Laws

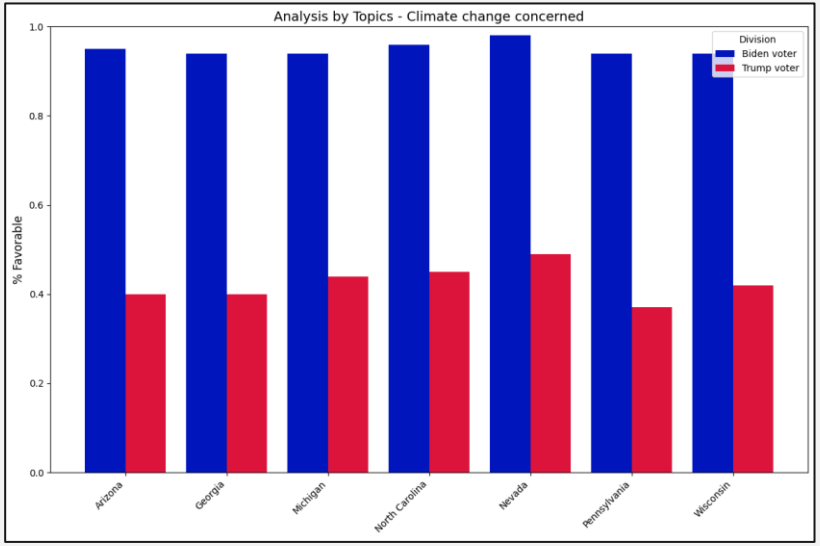


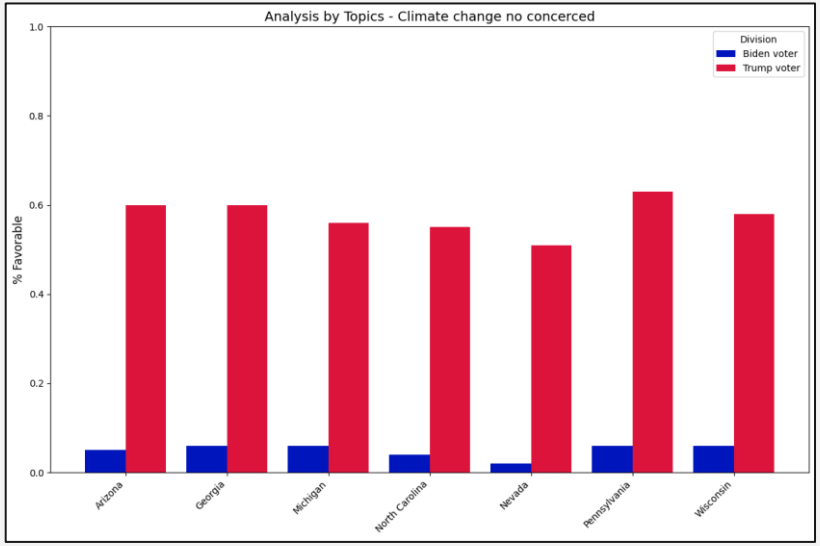






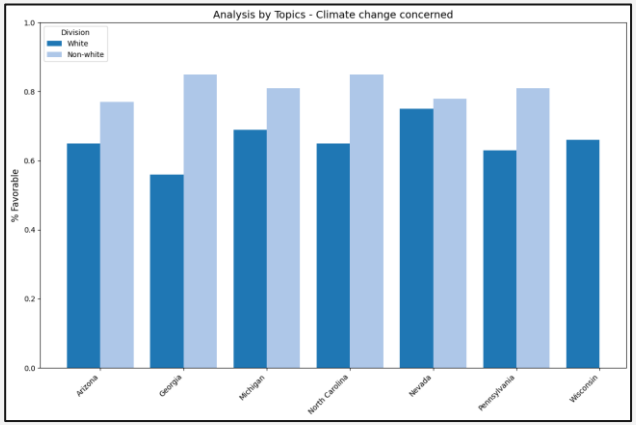
Analysis by topics – Climate Change

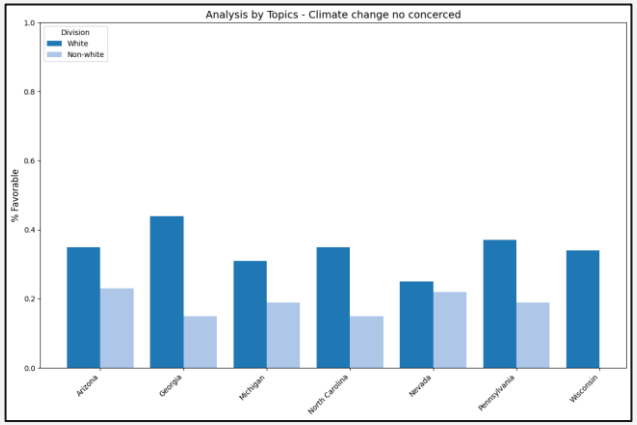


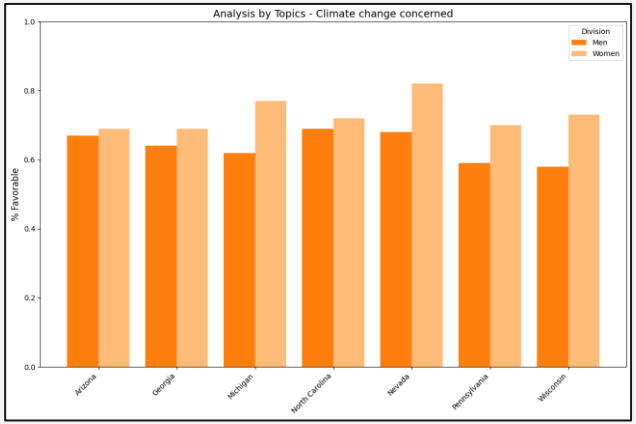


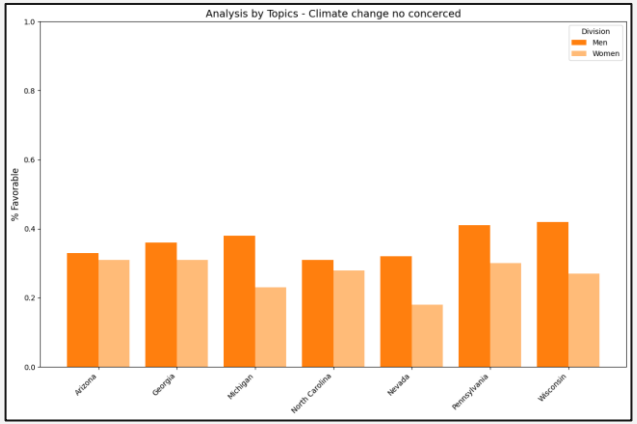
Almost all Biden voters are extremely concerned about climate change. Republicans are more divided on the issue.

Analysis by topics – Climate Change

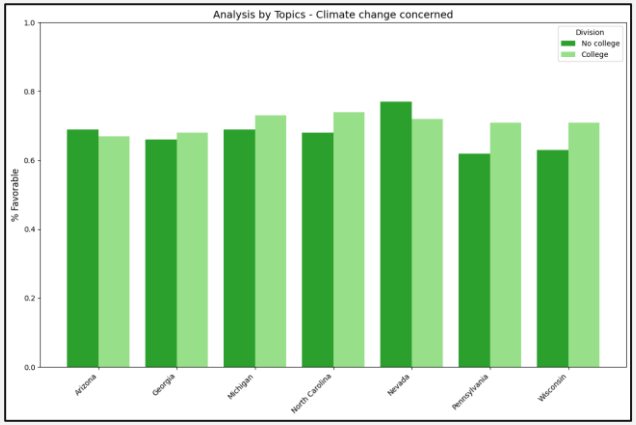


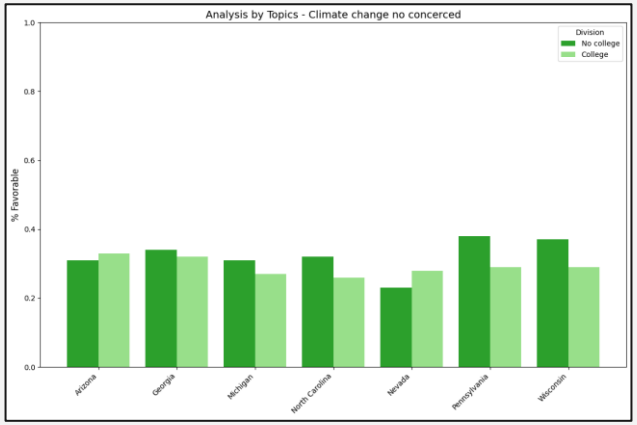


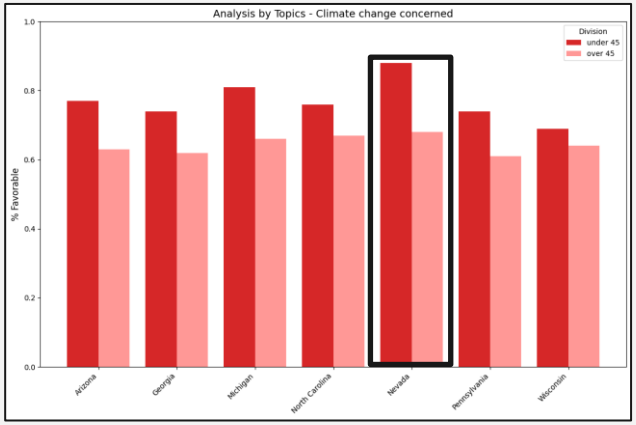


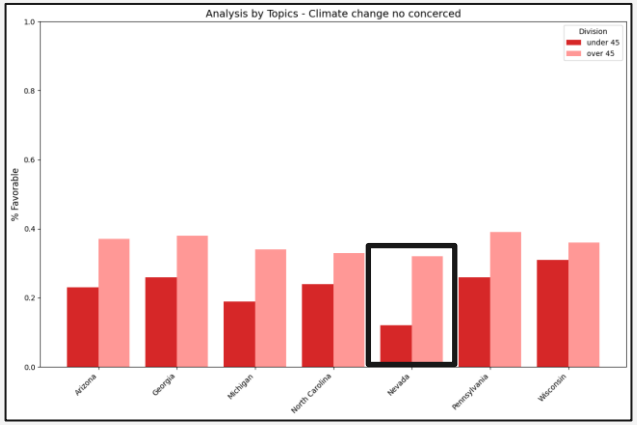


Analysis by topics – Climate Change

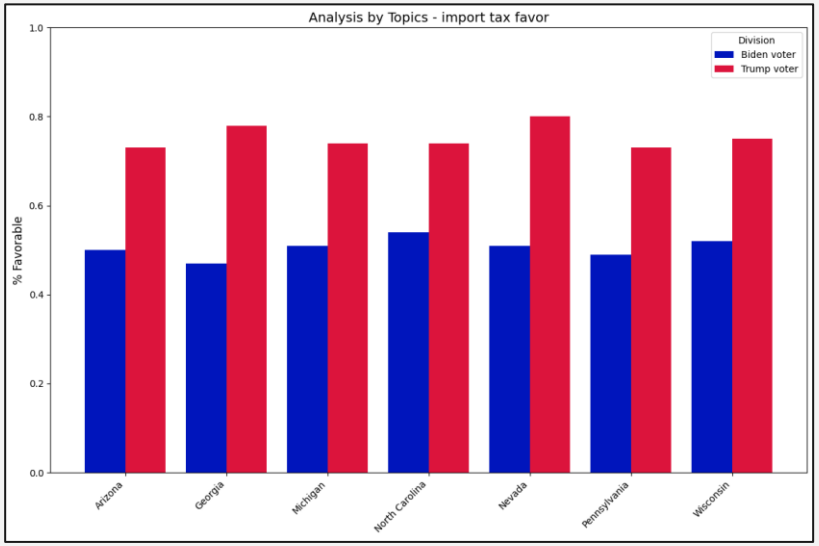


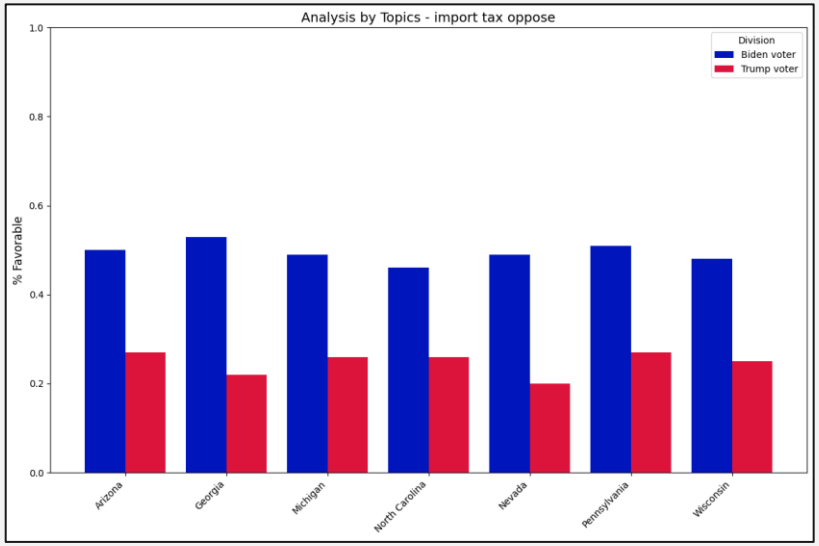






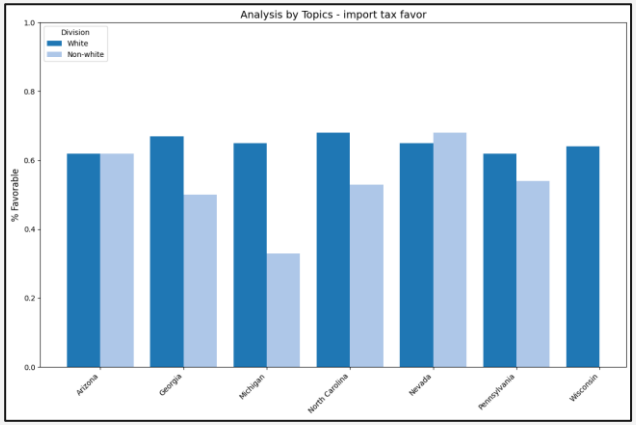
Analysis by topics – Import Tax

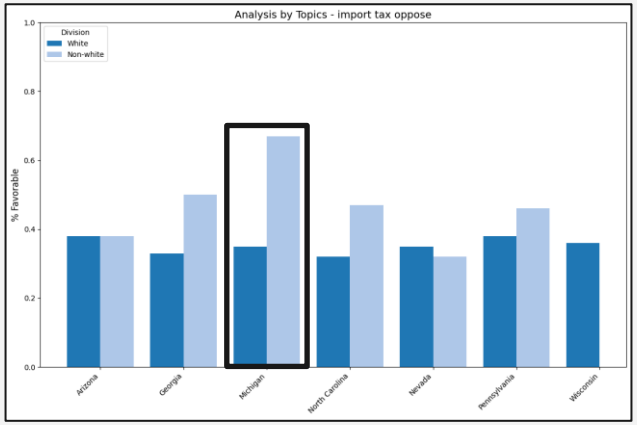


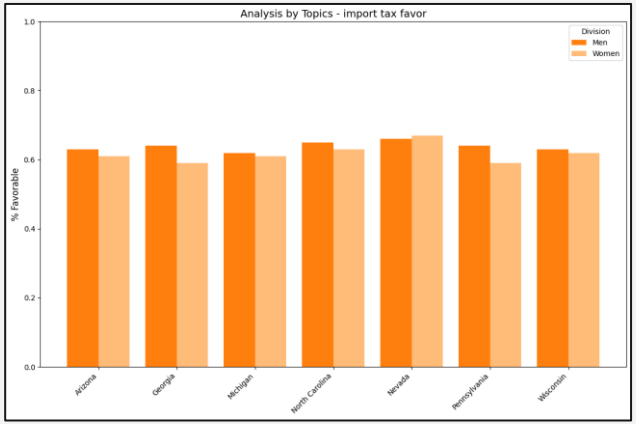


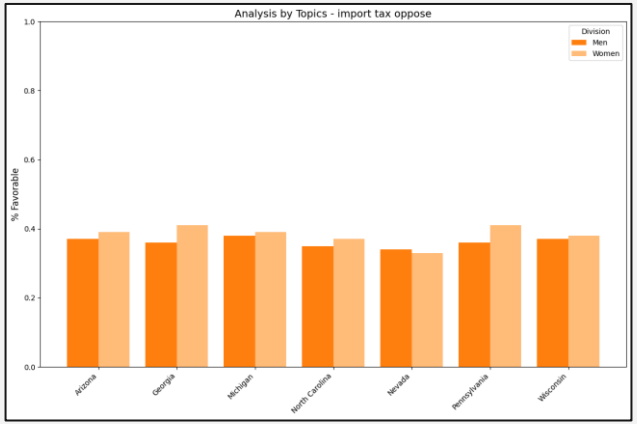
On the topic of tariffs, Democrats are evenly split, whereas Republicans show greater consensus in favor of tariffs.

Analysis by topics – Import Tax

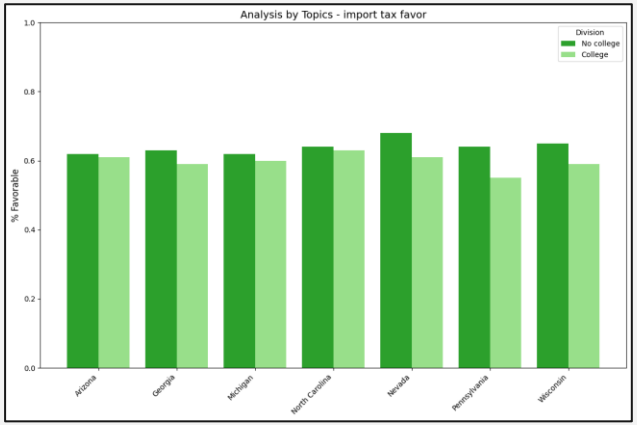


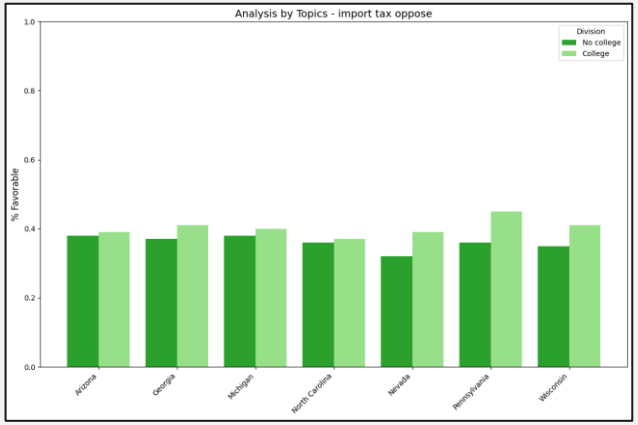


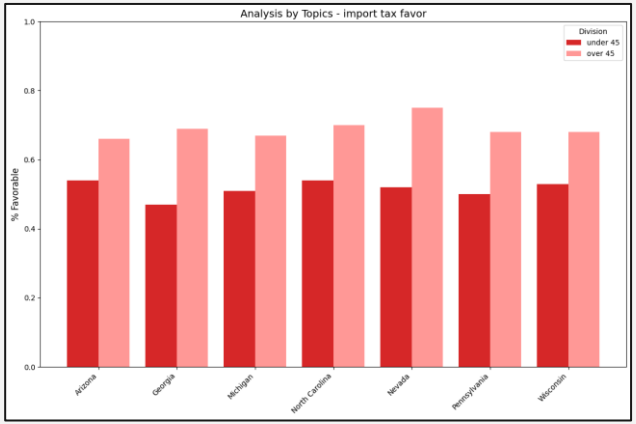


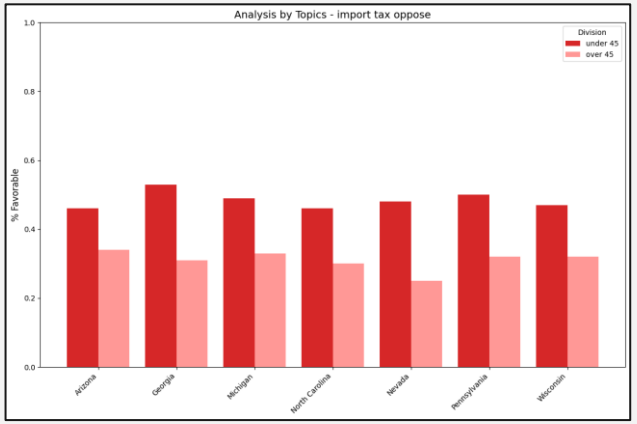


Analysis by topics – Import Tax





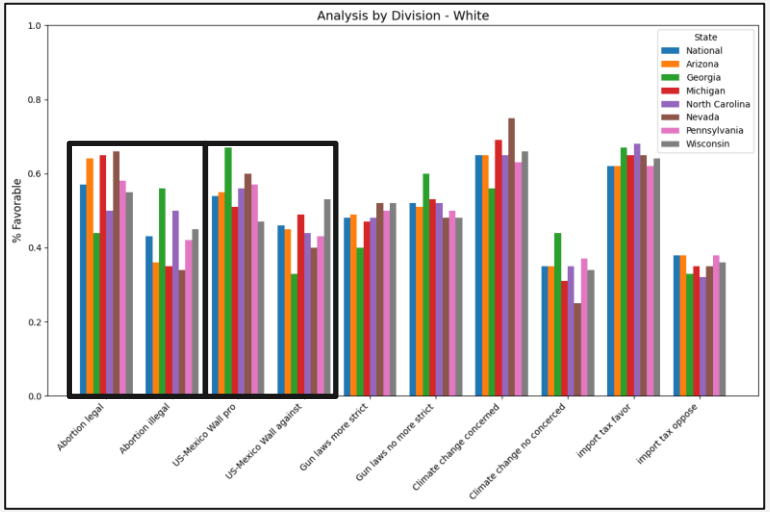


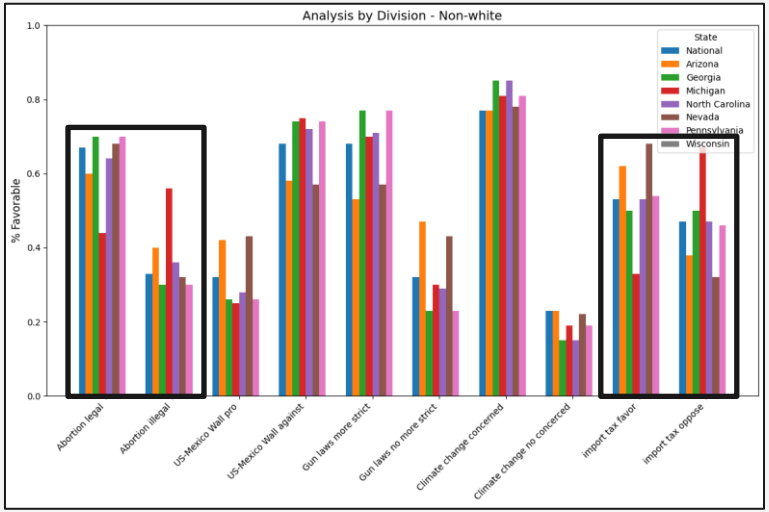


Social main topics– Analysis by population segment

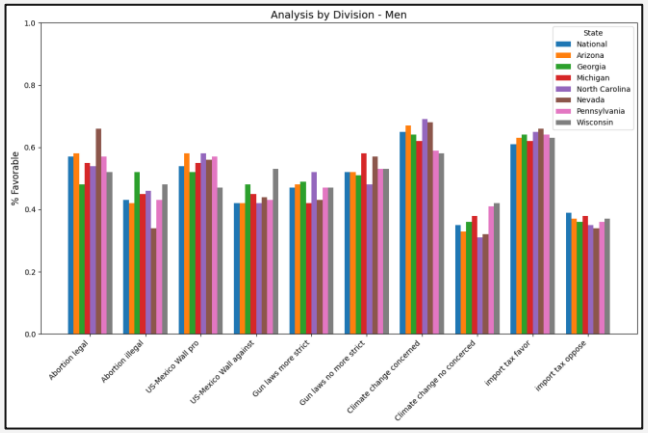
```
def division_analysis():
    divisions = df['Division'].unique()
    for division in divisions:
        division_data = df[df['Division'] == division]
        melted_data = division_data.melt(id_vars=['State', 'Division'],
                                         var_name='Theme',
                                         value_name='Percentage')
        themes = melted_data['Theme'].unique()
        states = melted_data['State'].unique()
        colors = plt.cm.tab20.colors[:len(states)]
        generic_analysis(melted_data, themes,
                         f'Analysis by Division - {division}',
                         states, None, 'State')

division_analysis()
```

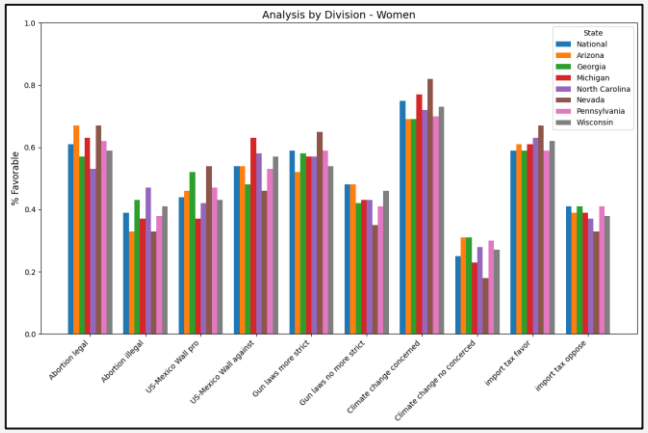
Differences between each topic.

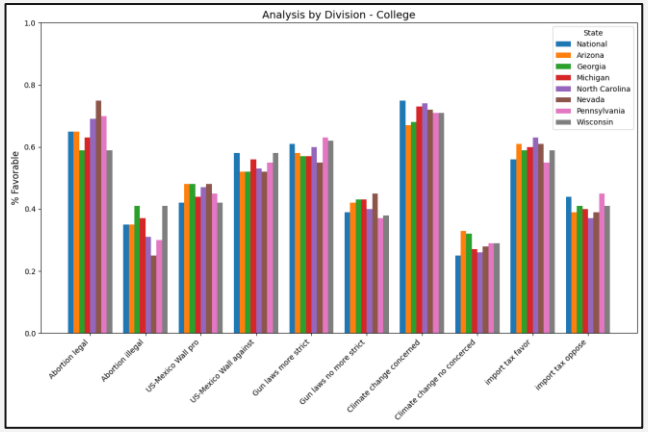


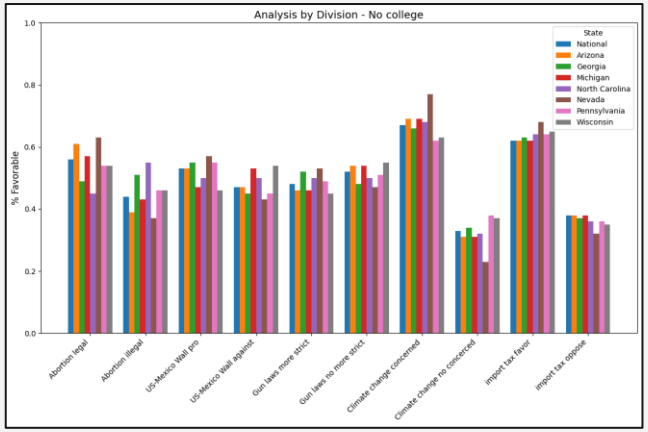


Social main topics– Analysis by topics

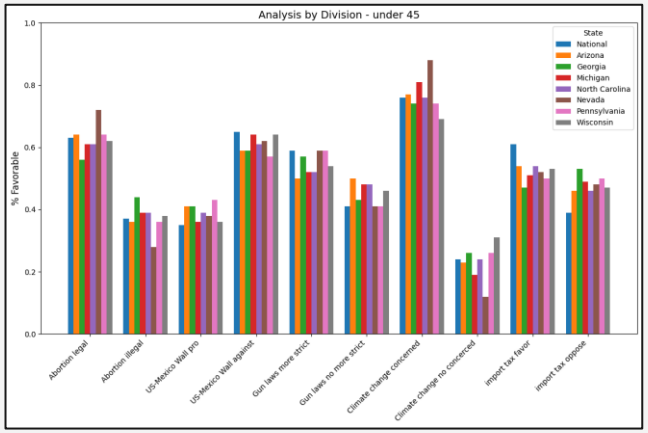


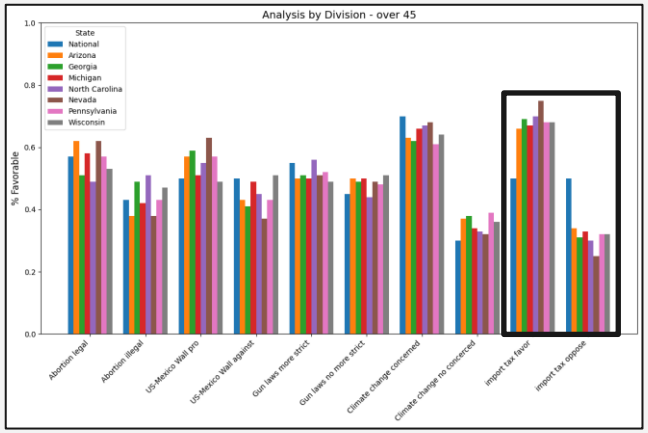


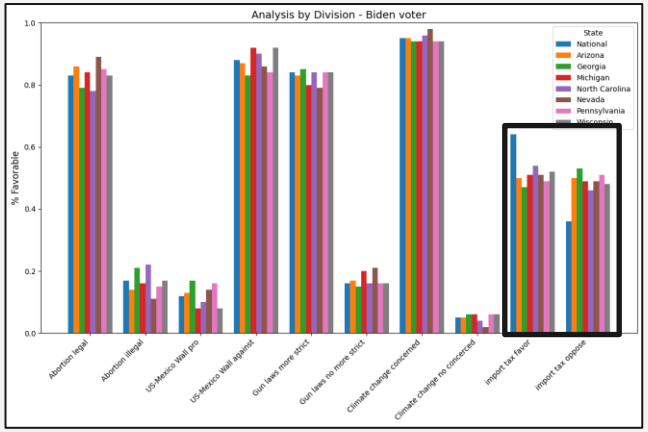


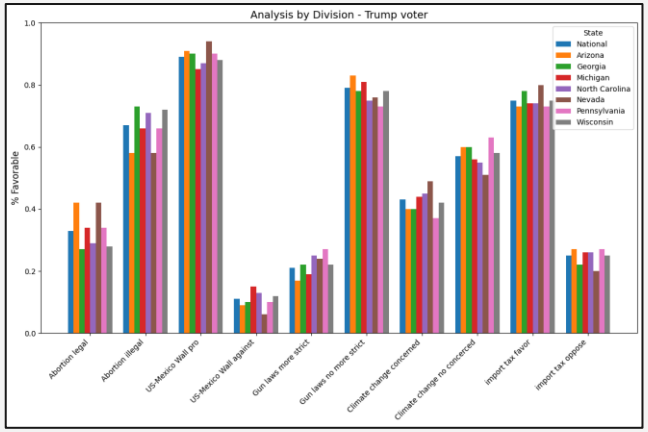


Social main topics– Analysis by topics









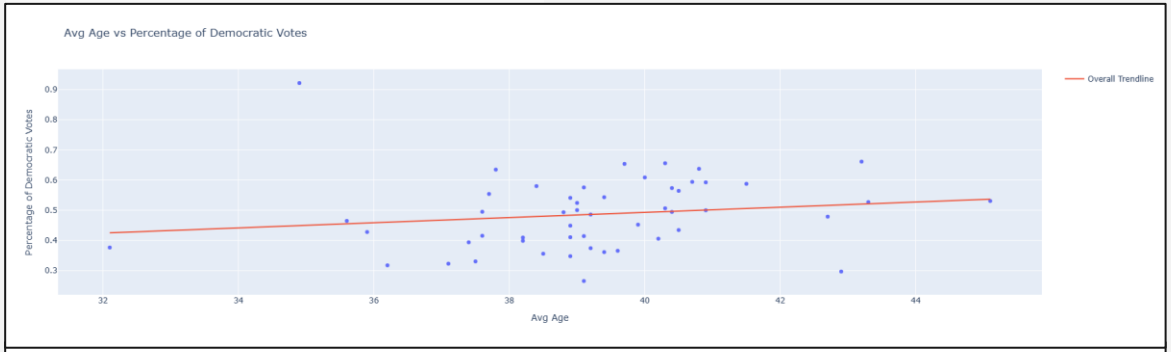
05

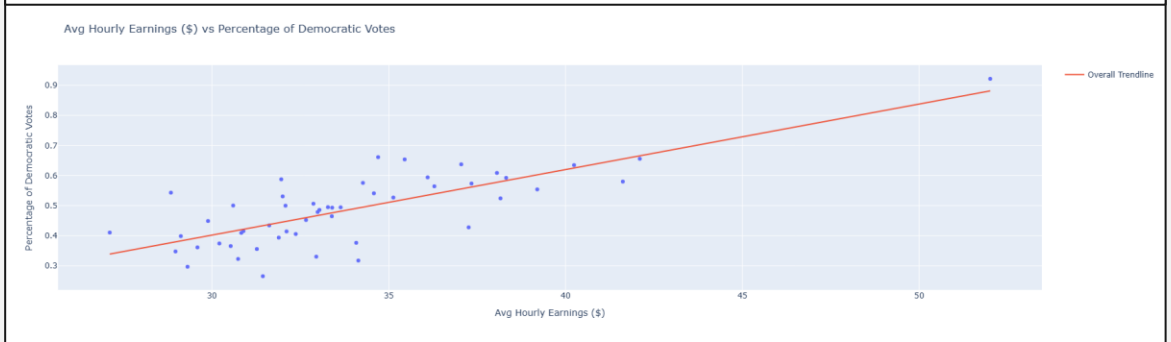
Linear regression

Linear regression

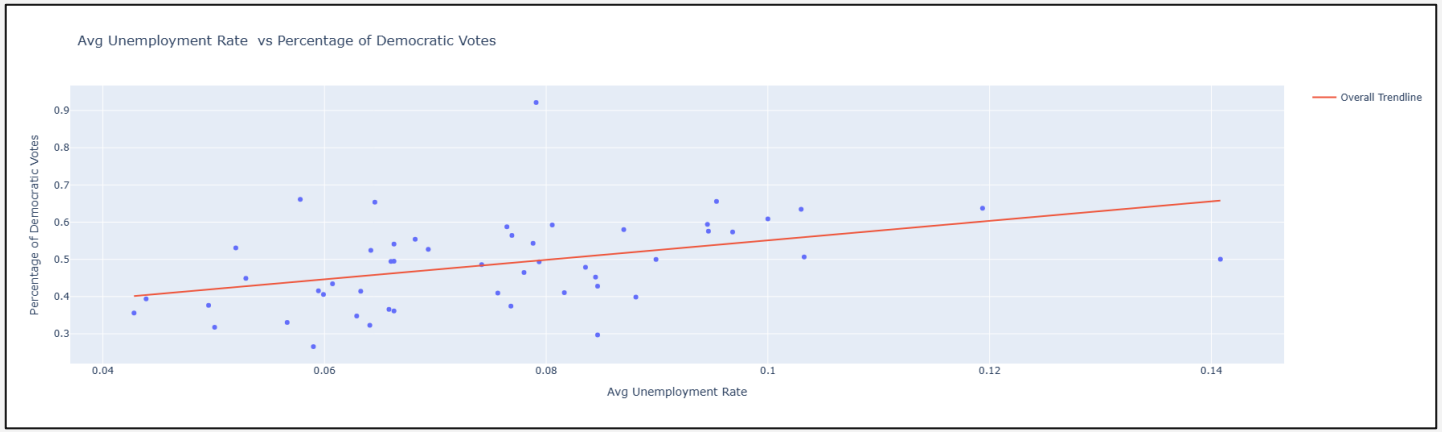
```
lst = [col for col in df.columns if col not in [df.columns[0], df.columns[1],
                                                df.columns[2], df.columns[3]]]

for i in lst:
    fig = px.scatter(
        x=df[i],
        y=df['% DEM 2020'],
        labels={'x': i, 'y': 'Percentage of Democratic Votes'},
        title=f"{i} vs Percentage of Democratic Votes",
        trendline  = 'ols', trendline_scope = 'overall')

    fig.show()
```

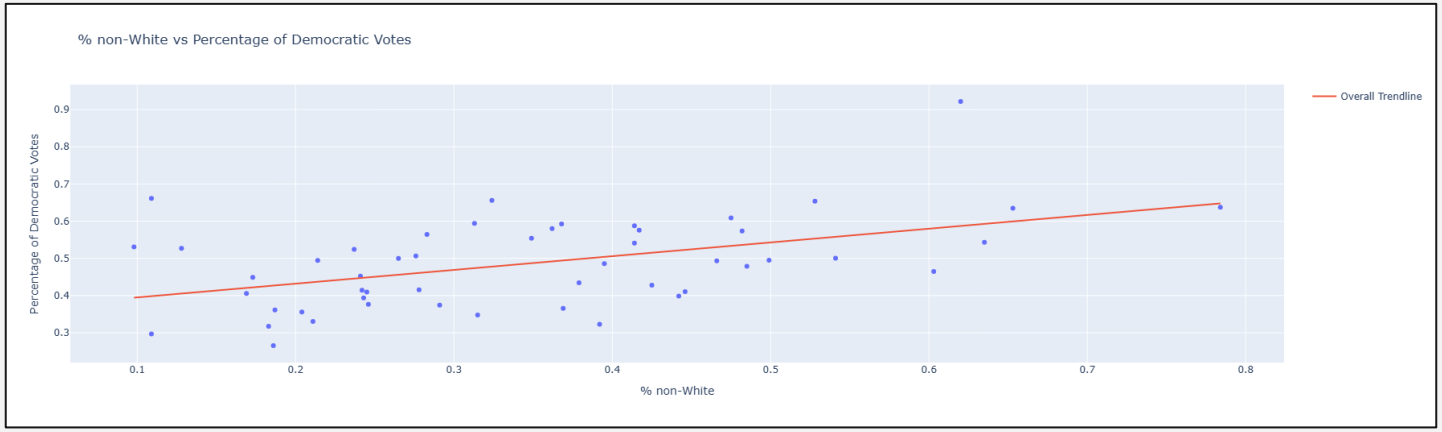
The code generates scatterplots to visualize the relationship between differnt independent variables and the percentage of Democratic votes (*% DEM 2020*).





Linear regression





Hypothesis test

```
y = df['% DEM 2020']

X = df[['Dem Historical Trend', 'Avg Age', 'Avg Hourly Earnings ($)',
        'Avg Unemployment Rate ', '% non-White']]
X = sm.add_constant(X)

model = sm.OLS(y, X).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             % DEM 2020   R-squared:                       0.832
Model:                            OLS   Adj. R-squared:                  0.813
Method:                 Least Squares   F-statistic:                     44.56
Date:                Tue, 21 Jan 2025   Prob (F-statistic):           2.50e-16
Time:                        10:42:43   Log-Likelihood:                 81.560
No. Observations:                  51   AIC:                            -151.1
Df Residuals:                      45   BIC:                            -139.5
Df Model:                           5
Covariance Type:            nonrobust
================================================================================================
                                   coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------------
const                           -0.6785      0.217     -3.131      0.003      -1.115      -0.242
Dem Historical Trend             0.0732      0.023      3.221      0.002       0.027       0.119
Avg Age                          0.0140      0.004      3.140      0.003       0.005       0.023
Avg Hourly Earnings ($)          0.0157      0.002      6.501      0.000       0.011       0.021
Avg Unemployment Rate           -0.3661      0.522     -0.701      0.487      -1.418       0.686
% non-White                      0.2397      0.067      3.580      0.001       0.105       0.375
==============================================================================
Omnibus:                        0.250   Durbin-Watson:                   1.935
Prob(Omnibus):                  0.883   Jarque-Bera (JB):                0.312
Skew:                           0.155   Prob(JB):                        0.856
Kurtosis:                       2.774   Cond. No.                     3.74e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.74e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

The values of the p-values indicate that the variables are statistically significant, except for the *unemployment rate*, which has a p-value of **48.7%**, leading to the conclusion that the null hypothesis of no influence on the dependent variable is not rejected. Other useful statistical variables for interpreting the model include the R-squared (0.832), which indicates that **83.2%** of the variability in the dependent variable is explained by the model, and the F-statistic, along with its p-value, which indicates that the model is statistically significant.

06

Conclusions

Summary of topics analyzed

1 Economic Topic

Analyzing the economic variables we could observe some differences following the elections. For employment, there was an increase, which benefited all ethnic groups. The unemployment rate, despite the strong increase in 2020 due to COVID-19, in the face of Biden's presidency there was a notable decrease during the months of 2021. For the weekly earnings, only Asians experienced modest changes, while each state increased its average weekly wage over the following two years. The consumer price index steadily increased, reaching its maximum peak in July 2022 with 9.1%, and then decreased over the following months.

2 Geographic topic

In 2020, voter turnout in the United States was around 67% of the population, and of this around 70% belong to the *White* category. In the seven swing states identified, the white population generally tends to favor the Republican Party, while other ethnic entities, such as blacks and hispanics, are more tied to the Democratic Party. These data suggest an important electoral dynamic in which the ethnic composition of the population plays a crucial role in political preferences, particularly in key states such as those defined as swing states.

3 Social Topic

In the analysis of the main issues addressed in the 2020 elections, it merged that Biden and Trump voters are extremely divided in the various segments. Analyzing, instead, the various segmentations of population, it emerged that the difference was made by *White-Non White* segmentation, despite the others analyzed in the graphs.

4 Historical topic

The voting history of a particular state significantly influences the percentages of votes obtained by the parties. This is easily inferred not only from the distribution of the boxplots but also from the univariate regression analysis, which highlights a strong statistical significance that is maintained even in the multivariate regression.

Thanks for your attention!

Angeletti Giacomo

Bertolini Tobia

Data Analytics for Business and Society
Computer Programming and Data Management
print("group name")

Cattelan Lorenzo

Zoccarato Mattia