In [ ]:
```
### Union Prediction for 2028 by State
```

In [ ]:
```

```

In [1]:
```
# Replace with your BLS API key
api_key = '059cdf7aeb7b4eaba4b01ca1676eb0da'
```

In [2]:
```
# Import Packages
import requests
import json
import prettytable
import pandas as pd
import matplotlib.pyplot as plt
import geopandas as gpd
import numpy as np
import seaborn as sns
```

In [3]:
```
# Upload data | I maxed out my api attempts mutiplue days trying to figure it out, so I just downloaded everything
all_df = pd.read_csv('/Users/Malloryh5/Downloads/lu.data.0.Current', delimiter='\t')
# Print Column names
all_df.columns
```

Out[3]:
```
Index(['series_id        ', 'year', 'period', '       value',
       'footnote_codes'],
      dtype='object')
```

In [4]:
```
#Check
all_df
```

Out[4]:

	series_id	year	period	value	footnote_codes
0	LUU0202851800	1995	A01	18342	5.0
1	LUU0202851800	1996	A01	18191	5.0
2	LUU0202851800	1997	A01	18147	5.0
3	LUU0202851800	1998	A01	18401	5.0
4	LUU0202851800	1999	A01	18938	5.0
...	...	...	...	...	...
29678	LUU0264899700	2019	A01	6.4	NaN
29679	LUU0264899700	2020	A01	6.6	NaN
29680	LUU0264899700	2021	A01	6.9	NaN
29681	LUU0264899700	2022	A01	6.3	NaN
29682	LUU0264899700	2023	A01	5.9	NaN

29683 rows × 5 columns

In [5]:
```
# Fix Column names
all_df.rename(columns=lambda x: x.replace(' ', ''), inplace=True)
```

In [6]:
```
# new column names for all data to split series_id
series = ['survey', 'Seasonal(code)', 'stype', 'lfst_code', 'seq_code', 'fips_code']
```

In [7]:
```
# Split series_id into 6 different columns
all_df[series] = all_df['series_id'].str.extract(r'(\w{2})(\w)(\d)(\d{2})(\d{5})(\d{2})')
```

In [8]:
```
#check
all_df
```

Out[8]:

	series_id	year	period	value	footnote_codes	survey	Seasonal(code)	stype	lfst_code	seq_code	fips_code
0	LUU0202851800	1995	A01	18342	5.0	LU	U	0	20	28518	00
1	LUU0202851800	1996	A01	18191	5.0	LU	U	0	20	28518	00
2	LUU0202851800	1997	A01	18147	5.0	LU	U	0	20	28518	00
3	LUU0202851800	1998	A01	18401	5.0	LU	U	0	20	28518	00
4	LUU0202851800	1999	A01	18938	5.0	LU	U	0	20	28518	00
...	...	...	...	...	...	...	...	...	...	...	...
29678	LUU0264899700	2019	A01	6.4	NaN	LU	U	0	26	48997	00
29679	LUU0264899700	2020	A01	6.6	NaN	LU	U	0	26	48997	00
29680	LUU0264899700	2021	A01	6.9	NaN	LU	U	0	26	48997	00
29681	LUU0264899700	2022	A01	6.3	NaN	LU	U	0	26	48997	00
29682	LUU0264899700	2023	A01	5.9	NaN	LU	U	0	26	48997	00

29683 rows × 11 columns

In [9]:
```
# Check if there is an seasonal data
if 'S' in all_df['Seasonal(code)'].values:
    print("Seasonal data")
else:
    print("No seasonal data")
```

```
No seasonal data
```

In [10]:
```
# Delete unneeded columns
# list to drop
drop_df = ['survey', 'Seasonal(code)']
# Drop
all_df = all_df.drop(columns = drop_df)
```

In [11]:
```
# Print dataframe
all_df
```

Out[11]:
```
           series_id  year  period  value  footnote_codes  stype  lfst_code  seq_code  fips_code
    0  LUU0202851800  1995     A01  18342             5.0      0         20     28518         00
    1  LUU0202851800  1996     A01  18191             5.0      0         20     28518         00
    2  LUU0202851800  1997     A01  18147             5.0      0         20     28518         00
    3  LUU0202851800  1998     A01  18401             5.0      0         20     28518         00
    4  LUU0202851800  1999     A01  18938             5.0      0         20     28518         00
  ...            ...   ...     ...    ...             ...    ...        ...       ...        ...
29678  LUU0264899700  2019     A01    6.4             NaN      0         26     48997         00
29679  LUU0264899700  2020     A01    6.6             NaN      0         26     48997         00
29680  LUU0264899700  2021     A01    6.9             NaN      0         26     48997         00
29681  LUU0264899700  2022     A01    6.3             NaN      0         26     48997         00
29682  LUU0264899700  2023     A01    5.9             NaN      0         26     48997         00

29683 rows × 9 columns
```

In [12]:
```
# make value numeric
all_df['value'] = pd.to_numeric(all_df['value'], errors='coerce')
```

In [13]:
```
# Convert 'year' column to integer if it's not already
all_df['year'] = all_df['year'].astype(int)
# Convert 'value' column to float if it's not already
all_df['value'] = all_df['value'].astype(float)
```

In [14]:
```
# Keys
df_seasonal = pd.read_csv('/Users/Malloryh5/Downloads/lu.seasonal', delimiter='\t')
dfs_lfst = pd.read_csv('/Users/Malloryh5/Downloads/lu.lfst.txt', delimiter='\t')
dft_seq = pd.read_csv('/Users/Malloryh5/Downloads/lu.series', delimiter='\t')
dfs_fips = pd.read_csv('/Users/Malloryh5/Downloads/lu.fips', delimiter='\t')

# Keys for datasets
tdata_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.tdata', delimiter='\t')
pcts_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.pcts', delimiter='\t')
earn_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.earn', delimiter='\t')
class_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.class', delimiter='\t')
unin_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.unin', delimiter='\t')
indy_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.indy.txt', delimiter='\t')
occupation_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.occupation', delimiter='\t')
education_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.education', delimiter='\t')
ages_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.ages', delimiter='\t')
race_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.race', delimiter='\t')
orig_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.orig', delimiter='\t')
sexs_code = pd.read_csv('/Users/Malloryh5/Downloads/lu.sexs', delimiter='\t')
seasonal = pd.read_csv('/Users/Malloryh5/Downloads/lu.seasonal', delimiter='\t')
footnote_codes = pd.read_csv('/Users/Malloryh5/Downloads/lu.footnote', delimiter='\t')
```

In [15]:
```
# review column names
dft_seq.columns
```

Out[15]:
```
Index(['series_id         ', 'lfst_code', 'fips_code', 'series_title',
       'tdata_code', 'pcts_code', 'earn_code', 'class_code', 'unin_code',
       'indy_code', 'occupation_code', 'education_code', 'ages_code',
       'race_code', 'orig_code', 'sexs_code', 'seasonal', 'footnote_codes',
       'begin_year', 'begin_period', 'end_year', 'end_period'],
      dtype='object')
```

In [16]:
```
#Strip and remove all white space
dft_seq = dft_seq.rename(columns=lambda x: x.strip())
dft_seq['series_id'] = dft_seq['series_id'].str.strip()
dft_seq['series_title'] = dft_seq['series_title'].str.strip()
```

Are people who are part of a union paid more than non-union individuals or people represented by a union?

In [17]:
```
# Save just in case. Do not need to look at goverment, but keep in case, I change my mind
total_earnings = dft_seq[
    dft_seq['series_title'].str.contains('weekly earnings', case=False, na=False) &
    (dft_seq['occupation_code'] == 0) &
    (dft_seq['indy_code'] == 0) &
    (dft_seq['ages_code'] == 0) &
    (dft_seq['sexs_code'] == 0) &
    (dft_seq['race_code'] == 0) &
    (dft_seq['orig_code'] == 0) &
    (dft_seq['class_code'] == 16)
]
# Private sector
need_data_earnings = dft_seq[
    dft_seq['series_title'].str.contains('weekly earnings', case=False, na=False) &
    (dft_seq['occupation_code'] == 0) &
    (dft_seq['indy_code'] == 0) &
    (dft_seq['ages_code'] == 0) &
    (dft_seq['sexs_code'] == 0) &
    (dft_seq['race_code'] == 0) &
    (dft_seq['orig_code'] == 0) &
    (dft_seq['class_code'] == 17)
]
```

In [18]:
```
# Remove white shace in column header
need_data_earnings.rename(columns=lambda x: x.replace(' ', ''), inplace=True)
```

```
/var/folders/q9/wrynvqzj0dgb0yksnkbr0sj40000gn/T/ipykernel_9305/940145784.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  need_data_earnings.rename(columns=lambda x: x.replace(' ', ''), inplace=True)
```

In [19]:
```python
# List of series that needs to be pulled
series_id_earning = need_data_earnings['series_id'].unique().tolist()
# List of year that needs to be pulled
year = list(range(2014,2024))
```

In [20]:
```python
# Remove spaces
series_id_earning = [x.replace(' ', '') for x in series_id_earning]
```

In [21]:
```python
# Strip white space
all_df['series_id'] = all_df['series_id'].str.strip()
```

In [22]:
```python
# Pull data that is only in series list
df_earnings = all_df[all_df['series_id'].isin(series_id_earning)]
# Pull data that is only in year list
df_earnings = (df_earnings[df_earnings['year'].isin(year)])
```

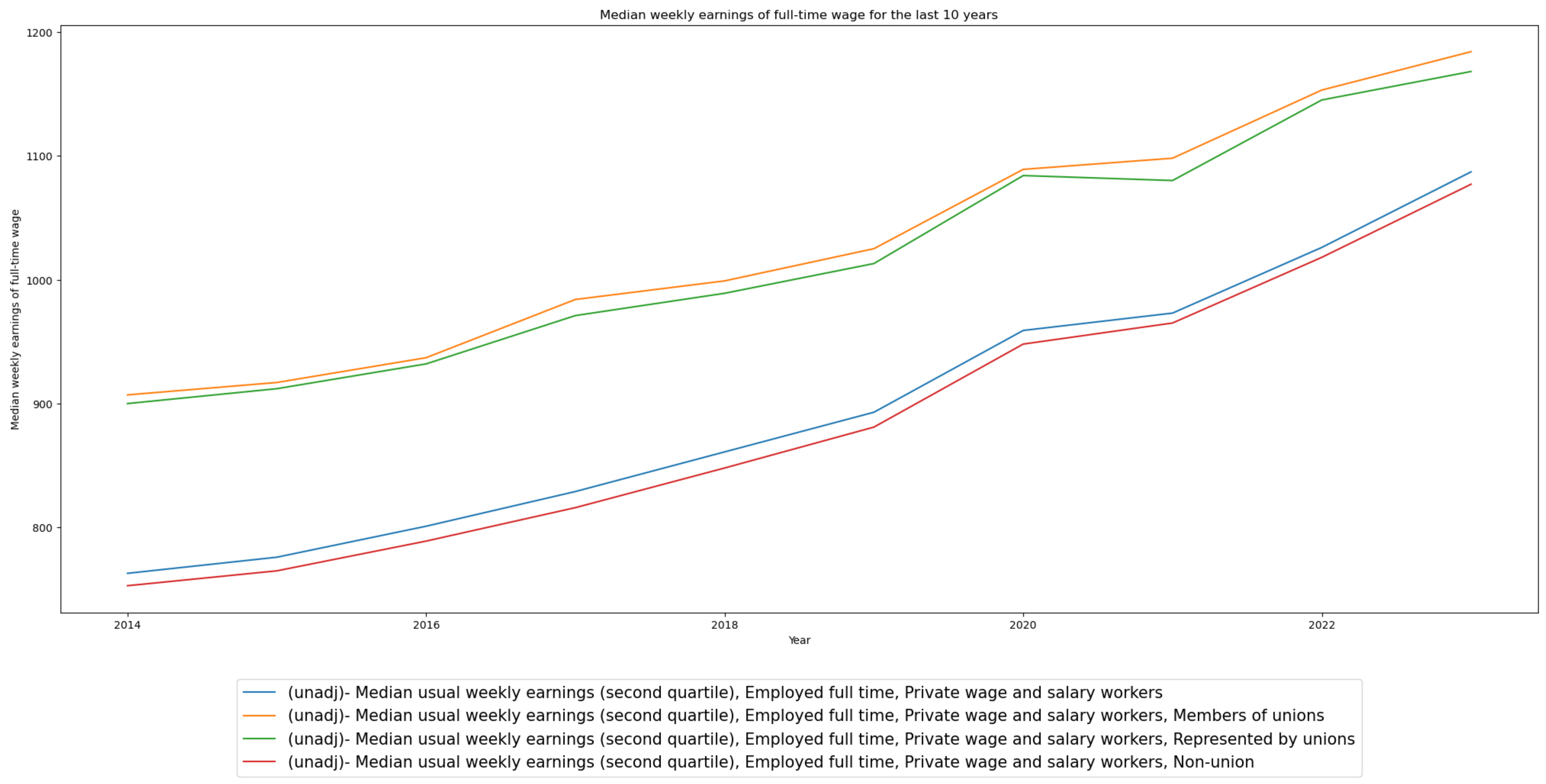
In [23]:
```python
#Check
df_earnings
```

Out[23]:

	series_id	year	period	value	footnote_codes	stype	lfst_code	seq_code	fips_code
21993	LUU0253191200	2014	A01	763.0	NaN	0	25	31912	00
21994	LUU0253191200	2015	A01	776.0	NaN	0	25	31912	00
21995	LUU0253191200	2016	A01	801.0	NaN	0	25	31912	00
21996	LUU0253191200	2017	A01	829.0	NaN	0	25	31912	00
21997	LUU0253191200	2018	A01	861.0	NaN	0	25	31912	00
21998	LUU0253191200	2019	A01	893.0	NaN	0	25	31912	00
21999	LUU0253191200	2020	A01	959.0	NaN	0	25	31912	00
22000	LUU0253191200	2021	A01	973.0	NaN	0	25	31912	00
22001	LUU0253191200	2022	A01	1026.0	NaN	0	25	31912	00
22002	LUU0253191200	2023	A01	1087.0	NaN	0	25	31912	00
22017	LUU0253191300	2014	A01	907.0	NaN	0	25	31913	00
22018	LUU0253191300	2015	A01	917.0	NaN	0	25	31913	00
22019	LUU0253191300	2016	A01	937.0	NaN	0	25	31913	00
22020	LUU0253191300	2017	A01	984.0	NaN	0	25	31913	00
22021	LUU0253191300	2018	A01	999.0	NaN	0	25	31913	00
22022	LUU0253191300	2019	A01	1025.0	NaN	0	25	31913	00
22023	LUU0253191300	2020	A01	1089.0	NaN	0	25	31913	00
22024	LUU0253191300	2021	A01	1098.0	NaN	0	25	31913	00
22025	LUU0253191300	2022	A01	1153.0	NaN	0	25	31913	00
22026	LUU0253191300	2023	A01	1184.0	NaN	0	25	31913	00
22041	LUU0253191400	2014	A01	900.0	NaN	0	25	31914	00
22042	LUU0253191400	2015	A01	912.0	NaN	0	25	31914	00
22043	LUU0253191400	2016	A01	932.0	NaN	0	25	31914	00
22044	LUU0253191400	2017	A01	971.0	NaN	0	25	31914	00
22045	LUU0253191400	2018	A01	989.0	NaN	0	25	31914	00
22046	LUU0253191400	2019	A01	1013.0	NaN	0	25	31914	00
22047	LUU0253191400	2020	A01	1084.0	NaN	0	25	31914	00
22048	LUU0253191400	2021	A01	1080.0	NaN	0	25	31914	00
22049	LUU0253191400	2022	A01	1145.0	NaN	0	25	31914	00
22050	LUU0253191400	2023	A01	1168.0	NaN	0	25	31914	00
22065	LUU0253191500	2014	A01	753.0	NaN	0	25	31915	00
22066	LUU0253191500	2015	A01	765.0	NaN	0	25	31915	00
22067	LUU0253191500	2016	A01	789.0	NaN	0	25	31915	00
22068	LUU0253191500	2017	A01	816.0	NaN	0	25	31915	00
22069	LUU0253191500	2018	A01	848.0	NaN	0	25	31915	00
22070	LUU0253191500	2019	A01	881.0	NaN	0	25	31915	00
22071	LUU0253191500	2020	A01	948.0	NaN	0	25	31915	00
22072	LUU0253191500	2021	A01	965.0	NaN	0	25	31915	00
22073	LUU0253191500	2022	A01	1018.0	NaN	0	25	31915	00
22074	LUU0253191500	2023	A01	1077.0	NaN	0	25	31915	00

In [24]:
```python
# Create a mapping
series_title_map = dict(zip(dft_seq['series_id'], dft_seq['series_title']))
```

In [25]:
```python
# Make table

#Size of graph
plt.figure(figsize=(25,10))

#For loop to make a line for every union option
for series in df_earnings['series_id'].unique():
    # for every series make a subset
    subset = df_earnings[df_earnings['series_id'] == series]
    # Use map for legend
    series_ledger = series_title_map.get(series, series)
    # plot line graph and group by label
    plt.plot(subset['year'], subset['value'], label=series_ledger)
# x-label
plt.xlabel('Year')
#y-label
plt.ylabel('Median weekly earnings of full-time wage')
#title
plt.title('Median weekly earnings of full-time wage for the last 10 years')
#legend
plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.1), fontsize=15)
#show
plt.show()
```



In [26]:
```python
# Make int
all_df['fips_code'] = all_df['fips_code'].astype(int)
```

States that are more likely to be part of a union?

In [27]:
```python
# List of wanted items
union_by_state_prisec = dft_seq[
    (dft_seq['sexs_code'] == 0) &
    (dft_seq['indy_code'] == 0) &
    (dft_seq['ages_code'] == 0) &
    (dft_seq['series_title'].str.contains('Percent of employed, ', case=False, na=False, regex=False)) &
    (dft_seq['race_code'] == 0) &
    (dft_seq['orig_code'] == 0) &
    (dft_seq['fips_code'].isin(range(1, 57)))
]
```

In [28]:
```python
#Print to check
union_by_state_prisec
```

Out[28]:

	series_id	lfst_code	fips_code	series_title	tdata_code	pcts_code	earn_code	class_code	unin_code	indy_code	...	ages_code	race_code	orig_code	s
458	LUU0204899601	20	1	(unadj)- Percent of employed, Members of union...	1	5	0	16	1	0	...	0	0	0	
459	LUU0204899602	20	2	(unadj)- Percent of employed, Members of union...	1	5	0	16	1	0	...	0	0	0	
460	LUU0204899604	20	4	(unadj)- Percent of employed, Members of union...	1	5	0	16	1	0	...	0	0	0	
461	LUU0204899605	20	5	(unadj)- Percent of employed, Members of union...	1	5	0	16	1	0	...	0	0	0	
462	LUU0204899606	20	6	(unadj)- Percent of employed, Members of union...	1	5	0	16	1	0	...	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
556	LUU0204899751	20	51	(unadj)- Percent of employed, Represented by u...	1	5	0	16	2	0	...	0	0	0	
557	LUU0204899753	20	53	(unadj)- Percent of employed, Represented by u...	1	5	0	16	2	0	...	0	0	0	
558	LUU0204899754	20	54	(unadj)- Percent of employed, Represented by u...	1	5	0	16	2	0	...	0	0	0	
559	LUU0204899755	20	55	(unadj)- Percent of employed, Represented by u...	1	5	0	16	2	0	...	0	0	0	
560	LUU0204899756	20	56	(unadj)- Percent of employed, Represented by u...	1	5	0	16	2	0	...	0	0	0	

102 rows × 22 columns

In [29]:
```python
# List of series that needs to be pulled
state_unique_id = union_by_state_prisec['series_id'].unique()

# List of year that needs to be pulled
year_state = [2013, 2018, 2023]
```

In [30]:
```python
# Drop Union code 3 and 0
unin_code_28 = unin_code.drop(index=[0,3]).copy()
```

In [31]:
```python
unin_code_28
```

Out[31]:

	unin_code	unin_text
1	1	Members of unions
2	2	Represented by unions

In [32]:
```python
# Pull data that is only in series list
state_union = all_df[
    all_df['series_id'].isin(state_unique_id) &
    all_df['year'].isin(year_state)
]
```

In [33]:
```python
# Check if it was donw right
state_union['fips_code'] = state_union['fips_code'].astype(int)
```

```
/var/folders/q9/wrynvqzj0dgb0yksnkbr0sj40000gn/T/ipykernel_9305/1963364285.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  state_union['fips_code'] = state_union['fips_code'].astype(int)
```

In [34]:
```python
# make dic of states
state_name = dict(zip(dfs_fips['fips_code'], dfs_fips['fips_text']))
```

In [35]:
```python
# Map file
us_map = gpd.read_file('/Users/Malloryh5/Downloads/cb_2018_us_state_5m/cb_2018_us_state_5m.shp')
```

In [36]:
```python
# map names
state_union['state_name'] = state_union['fips_code'].map(state_name)
```

```
/var/folders/q9/wrynvqzj0dgb0yksnkbr0sj40000gn/T/ipykernel_9305/3537762183.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  state_union['state_name'] = state_union['fips_code'].map(state_name)
```

In [37]:
```python
# Add union code to list of data
merged_df = state_union.merge(union_by_state_prisec[['series_id', 'unin_code']], on='series_id', how='left')
# Check table
merged_df
```

Out[37]:

	series_id	year	period	value	footnote_codes	stype	lfst_code	seq_code	fips_code	state_name	unin_code
0	LUU0204899601	2013	A01	10.7	NaN	0	20	48996	1	Alabama	1
1	LUU0204899601	2018	A01	9.2	NaN	0	20	48996	1	Alabama	1
2	LUU0204899601	2023	A01	7.5	NaN	0	20	48996	1	Alabama	1
3	LUU0204899602	2013	A01	23.1	NaN	0	20	48996	2	Alaska	1
4	LUU0204899602	2018	A01	18.5	NaN	0	20	48996	2	Alaska	1
...	...	...	...	...	...	...	...	...	...	...	...
301	LUU0204899755	2018	A01	8.6	NaN	0	20	48997	55	Wisconsin	2
302	LUU0204899755	2023	A01	8.4	NaN	0	20	48997	55	Wisconsin	2
303	LUU0204899756	2013	A01	6.4	NaN	0	20	48997	56	Wyoming	2
304	LUU0204899756	2018	A01	7.7	NaN	0	20	48997	56	Wyoming	2
305	LUU0204899756	2023	A01	6.6	NaN	0	20	48997	56	Wyoming	2

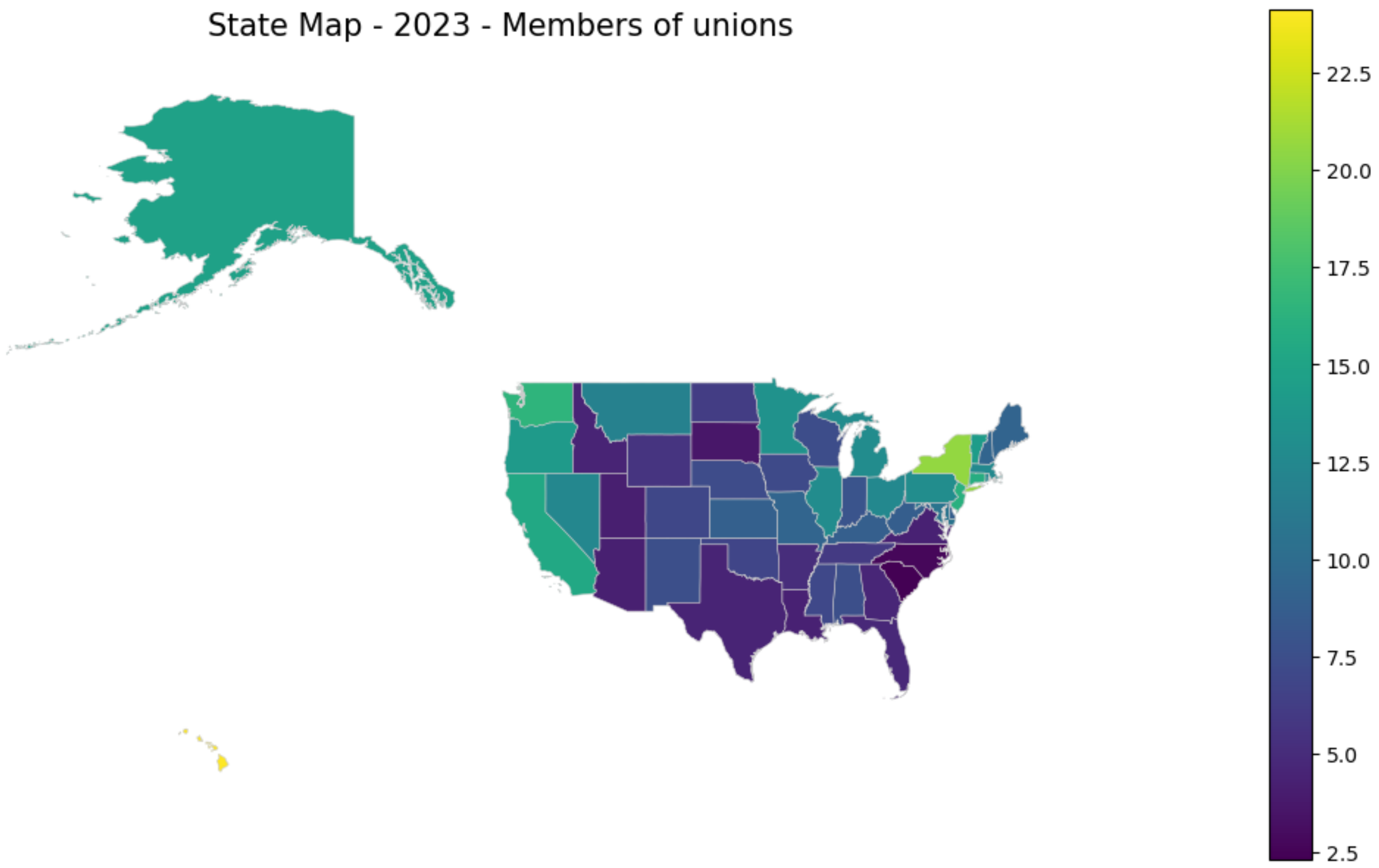
306 rows × 11 columns

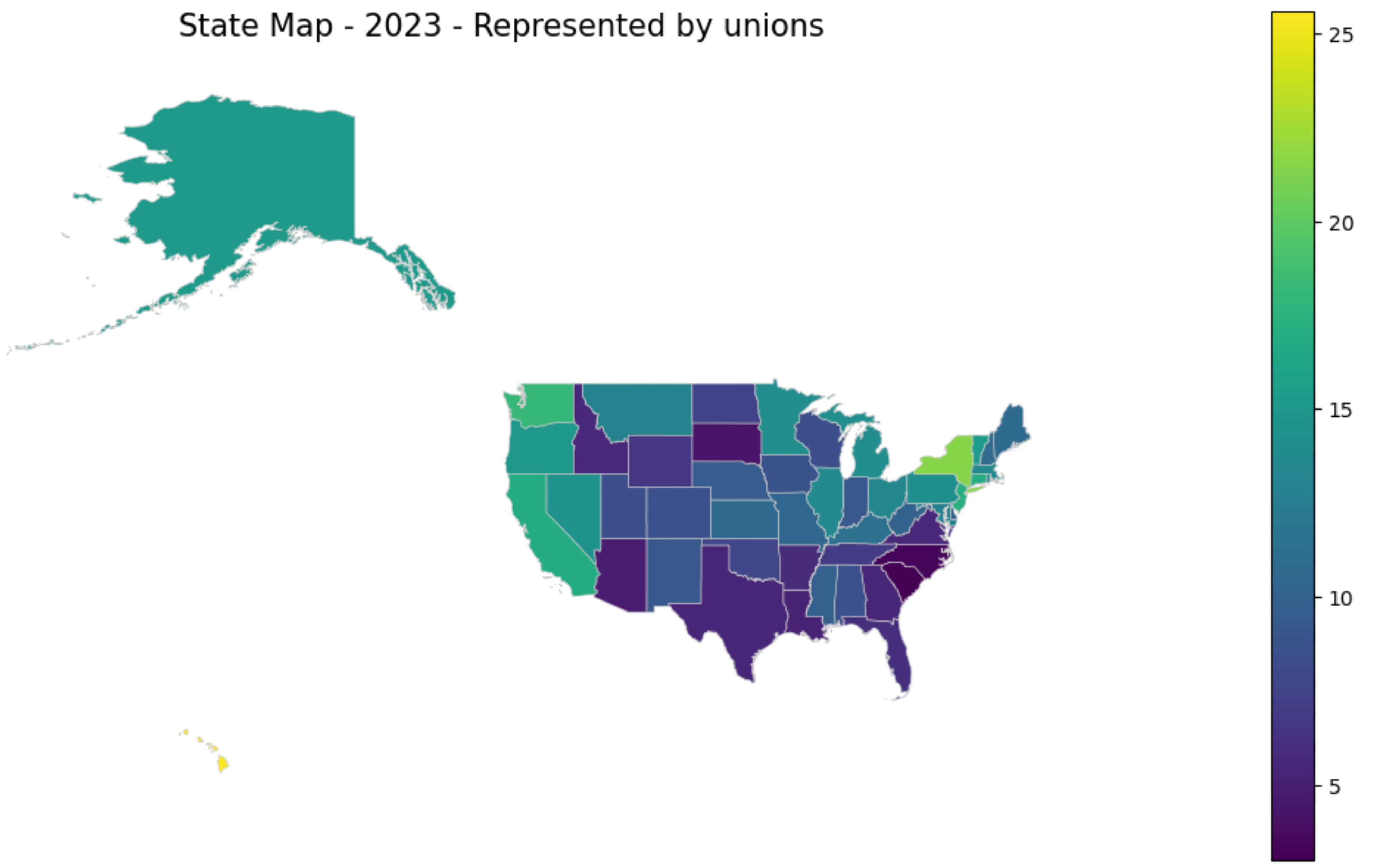
In [38]:
```python
# Make a legder code
unicode_titles_map = dict(zip(unin_code['unin_code'], unin_code['unin_text']))
```

In [39]:
```python
# Merge us_map with state_union_merge based on 'fips' and 'fips_code'
us_states_merged = pd.merge(us_map, merged_df, left_on='NAME', right_on='state_name', how='left')
```

In [40]:
```python
#year
year = 2023
# union codes
unique_codes = merged_df['unin_code'].unique()
```

In [41]:
```python
# for loop to plot people who are union and represented by a union on different maps
for code in unique_codes:
    # Filter the data for the current year and unique code
    year_data = us_states_merged[(us_states_merged['year'] == year) & (us_states_merged['unin_code'] == code)]

    # Create the plot
    fig, ax = plt.subplots(figsize=(15, 15))
    year_data.plot(column='value', cmap='viridis', linewidth=0.4, edgecolor='0.8', legend=True, legend_kwds={'shrink': 0.5}, ax=ax)

    # Set the title
    ax.set_title(f'State Map - {year} - {unicode_titles_map.get(code, "Unknown Code")}', fontsize=15)

    # Set axis limits
    ax.set_xlim(-200, -50)
    ax.set_ylim(15, 75)

    # Remove axis
    ax.set_xticks([])
    ax.set_yticks([])
    ax.set_axis_off()

    # Show the plot
    plt.show()
```





Demographics that is more likely to be part of a union?

In [42]:
```
# List of wanted items
dem_df = dft_seq[
    (~dft_seq['series_title'].str.contains('Employed wage and salary', case=False, na=False)) &
    (dft_seq['indy_code'] == 0) &
    (dft_seq['lfst_code'] == 20) &
    (dft_seq['earn_code'] == 0) &
    (dft_seq['fips_code'] == 0) &
    (dft_seq['tdata_code'] == 1) &
    (dft_seq['occupation_code'] == 0)
]
```

In [43]:
```
# Check problem
dem_df.columns
```

Out[43]:
```
Index(['series_id', 'lfst_code', 'fips_code', 'series_title', 'tdata_code',
       'pcts_code', 'earn_code', 'class_code', 'unin_code', 'indy_code',
       'occupation_code', 'education_code', 'ages_code', 'race_code',
       'orig_code', 'sexs_code', 'seasonal', 'footnote_codes', 'begin_year',
       'begin_period', 'end_year', 'end_period'],
      dtype='object')
```

In [44]:
```
# Remove white space
dem_df = dem_df.rename(columns=lambda x: x.replace(' ', ''))
```

In [45]:
```
# List of series that needs to be pulled
dem_unique_id = dem_df['series_id'].unique()

# List of year that needs to be pulled
year = list(range(2014,2024))
```

In [46]:
```
#Check list
dem_unique_id
```

Out[46]:
```
array(['LUU0204899600', 'LUU0204899700', 'LUU0204899800', 'LUU0204899900',
       'LUU0204900000', 'LUU0204900100', 'LUU0204900200', 'LUU0204900300',
       'LUU0204900400', 'LUU0204900500', 'LUU0204900600', 'LUU0204900700',
       'LUU0204900800', 'LUU0204900900', 'LUU0204901000', 'LUU0204901100',
       'LUU0204901200', 'LUU0204901300', 'LUU0204901400', 'LUU0204901500',
       'LUU0204901600', 'LUU0204901700', 'LUU0204901800', 'LUU0204901900',
       'LUU0204902000', 'LUU0204902100', 'LUU0204902200', 'LUU0204902300',
       'LUU0204902400', 'LUU0204902500', 'LUU0204902600', 'LUU0204902700',
       'LUU0204902800', 'LUU0204902900', 'LUU0204903000', 'LUU0204903100',
       'LUU0204903200', 'LUU0204903300', 'LUU0204903400', 'LUU0204903500',
       'LUU0204903600', 'LUU0204903700', 'LUU0204903800', 'LUU0204903900',
       'LUU0204904000', 'LUU0204904100', 'LUU0204904200', 'LUU0204904300',
       'LUU0204904400', 'LUU0204904500', 'LUU0204904600', 'LUU0204904700',
       'LUU0204904800', 'LUU0204904900', 'LUU0204905000', 'LUU0204905100',
       'LUU0204905200', 'LUU0204905300', 'LUU0204905400', 'LUU0204905500',
       'LUU0204905600', 'LUU0204905700', 'LUU0204905800', 'LUU0204905900',
       'LUU0204906000', 'LUU0204906100', 'LUU0204906600', 'LUU0204906700',
       'LUU0204906800', 'LUU0204906900', 'LUU0204907000', 'LUU0204907100',
       'LUU0204907200', 'LUU0204907300', 'LUU0204922700', 'LUU0204922900',
       'LUU0204923200', 'LUU0204923400', 'LUU0204923700', 'LUU0204923900',
       'LUU0204924200', 'LUU0204924400'], dtype=object)
```

In [47]:
```
# Pull data that is only in series list
dem_union = all_df[
    all_df['series_id'].isin(dem_unique_id) &
    all_df['year'].isin(year)
]
```

In [48]:
```
# Check table
dem_union
```

Out[48]:

	series_id	year	period	value	footnote_codes	stype	lfst_code	seq_code	fips_code
11052	LUU0204899600	2014	A01	11.1	NaN	0	20	48996	0
11053	LUU0204899600	2015	A01	11.1	NaN	0	20	48996	0
11054	LUU0204899600	2016	A01	10.7	NaN	0	20	48996	0
11055	LUU0204899600	2017	A01	10.7	NaN	0	20	48996	0
11056	LUU0204899600	2018	A01	10.5	NaN	0	20	48996	0
...	...	...	...	...	...	...	...	...	...
18950	LUU0204924400	2019	A01	43.0	NaN	0	20	49244	0
18951	LUU0204924400	2020	A01	45.1	NaN	0	20	49244	0
18952	LUU0204924400	2021	A01	43.9	NaN	0	20	49244	0
18953	LUU0204924400	2022	A01	42.7	NaN	0	20	49244	0
18954	LUU0204924400	2023	A01	41.7	NaN	0	20	49244	0

820 rows × 9 columns

In [49]:
```
# replace codes orig
orig_code['orig_code'].replace({0: 5, 1: 6}, inplace=True)
# replace code orig
dem_df['orig_code'].replace({0: 5, 1: 6}, inplace=True)

# replace codes race
race_code['race_code'].replace({0: 7, 1: 9}, inplace=True)
# replace code orig
dem_df['race_code'].replace({0: 7, 1: 9}, inplace=True)

# replace codes age
ages_code['ages_code'].replace({0: 8}, inplace=True)
# replace code age
dem_df['ages_code'].replace({0: 8}, inplace=True)
```

In [50]:
```
# items to remove
values_to_replace = {'ages_code': 8, 'race_code': 7, 'sexs_code': 0}

# For loop to remove values
for column, value in values_to_replace.items():
    # replace values and put nan for no values
    dem_df[column] = dem_df[column].replace(value, np.nan)
```

In [51]:
```
#dic for map
ages_code_map = dict(zip(ages_code['ages_code'],ages_code['ages_text']))
race_code_map = dict(zip(race_code['race_code'],race_code['race_text']))
orig_code_map = dict(zip(orig_code['orig_code'], orig_code['orig_text']))
sexs_code_map = dict(zip(sexs_code['sexs_code'], sexs_code['sexs_text']))

#Combine dict to make key
one_dict = {}
one_dict.update(orig_code_map)
one_dict.update(ages_code_map)
one_dict.update(race_code_map)
one_dict.update(sexs_code_map)
```

In [52]:
```
# merge certian columns
dem_union = dem_union.merge(dem_df[['series_id', 'ages_code','race_code','orig_code','sexs_code']], on='series_id', how='left')
```

In [53]:
```
#Review
one_dict
```

Out[53]:
```
{5: 'All Origins',
 6: 'Hispanic or Latino',
 8: '16 years and over',
 10: '16 to 24 years',
 28: '25 years and over',
 31: '25 to 34 years',
 38: '35 to 44 years',
 42: '45 to 54 years',
 49: '55 to 64 years',
 65: '65 years and over',
 7: 'All Races',
 9: 'White',
 3: 'Black or African American',
 4: 'Asian',
 0: 'Both Sexes',
 1: 'Men',
 2: 'Women'}
```

In [54]:
```
# Check table
dem_union
```

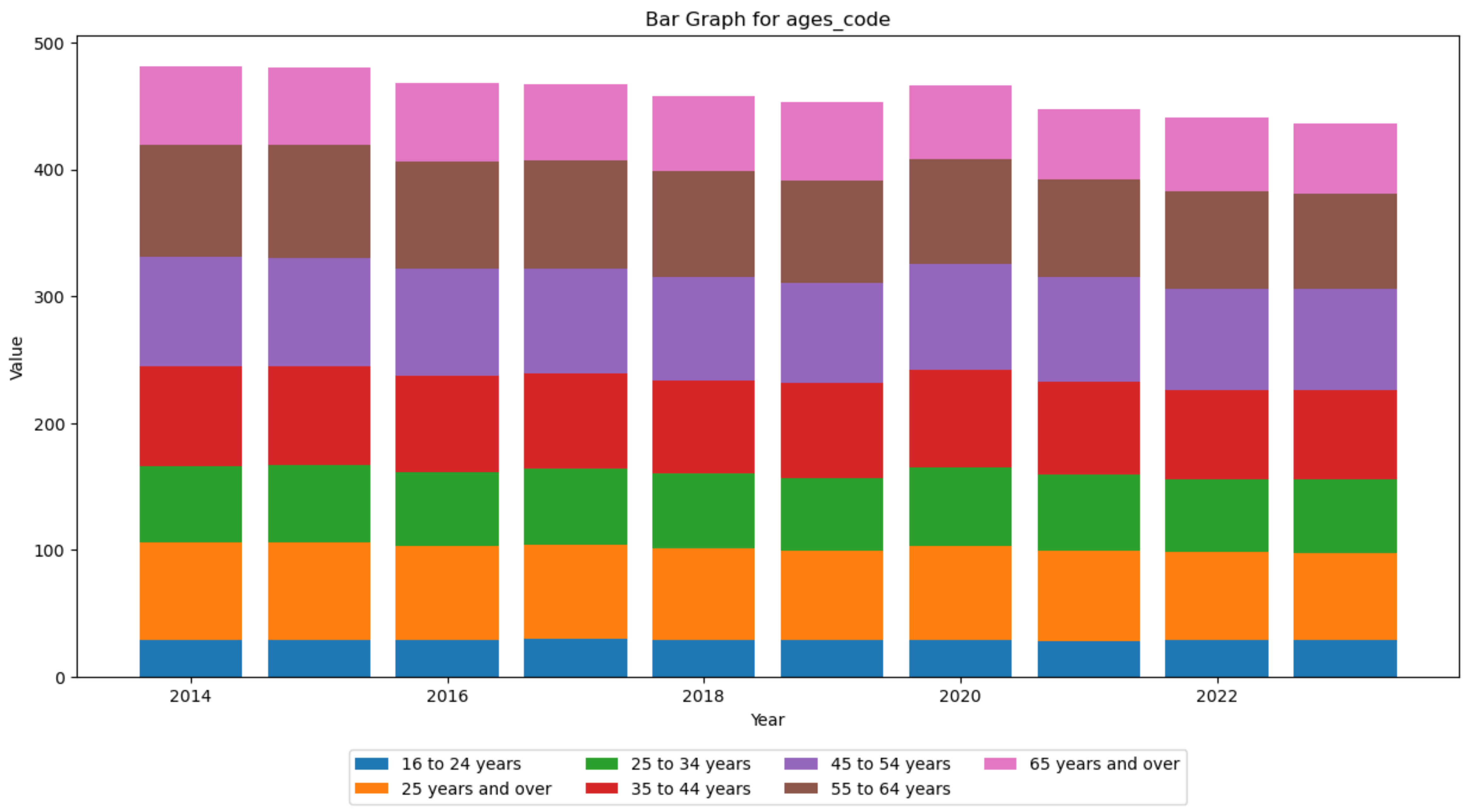
Out[54]:

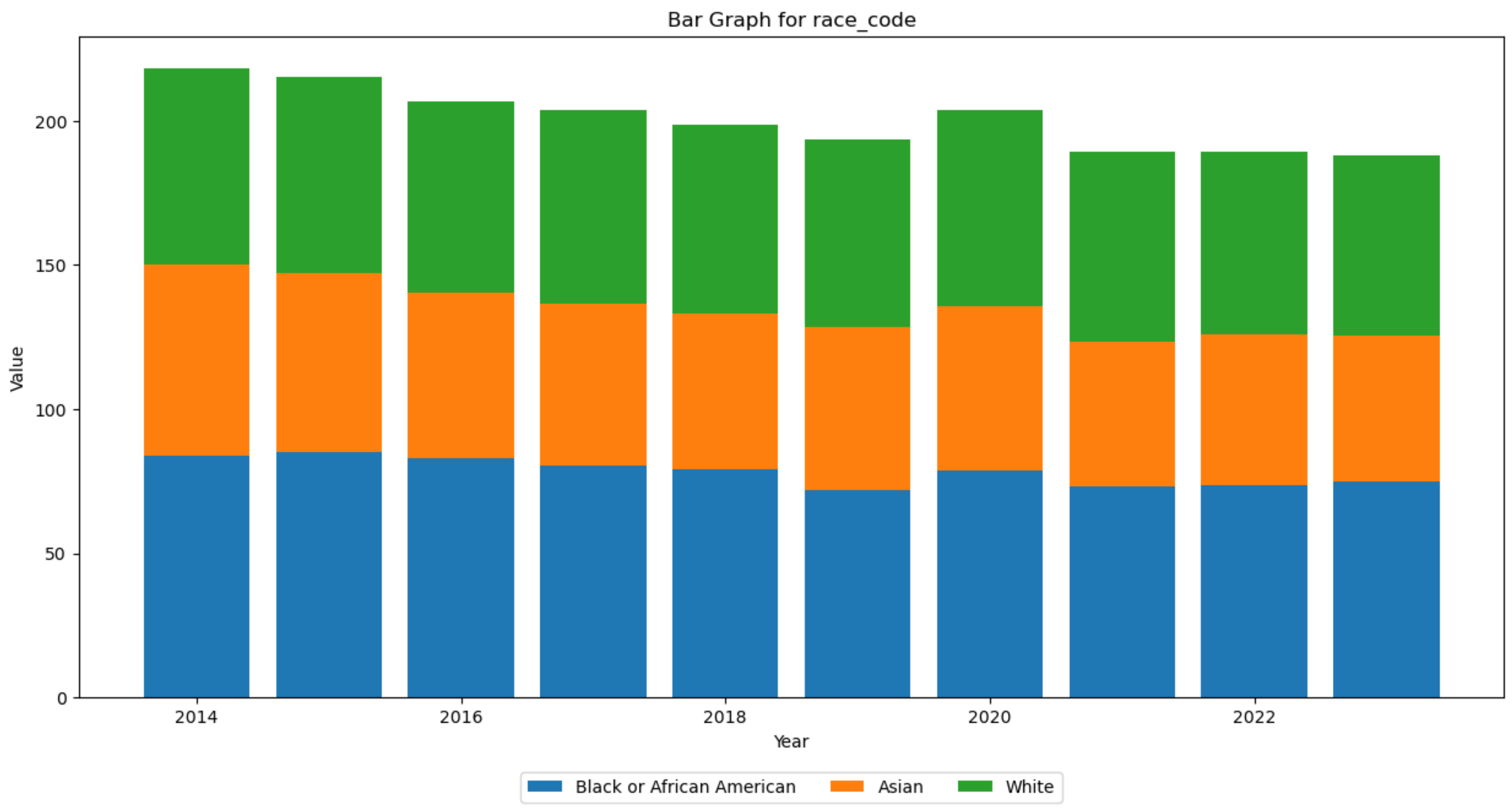
	series_id	year	period	value	footnote_codes	stype	lfst_code	seq_code	fips_code	ages_code	race_code	orig_code	sexs_code
0	LUU0204899600	2014	A01	11.1	NaN	0	20	48996	0	NaN	NaN	5	NaN
1	LUU0204899600	2015	A01	11.1	NaN	0	20	48996	0	NaN	NaN	5	NaN
2	LUU0204899600	2016	A01	10.7	NaN	0	20	48996	0	NaN	NaN	5	NaN
3	LUU0204899600	2017	A01	10.7	NaN	0	20	48996	0	NaN	NaN	5	NaN
4	LUU0204899600	2018	A01	10.5	NaN	0	20	48996	0	NaN	NaN	5	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...
815	LUU0204924400	2019	A01	43.0	NaN	0	20	49244	0	NaN	NaN	5	NaN
816	LUU0204924400	2020	A01	45.1	NaN	0	20	49244	0	NaN	NaN	5	NaN
817	LUU0204924400	2021	A01	43.9	NaN	0	20	49244	0	NaN	NaN	5	NaN
818	LUU0204924400	2022	A01	42.7	NaN	0	20	49244	0	NaN	NaN	5	NaN
819	LUU0204924400	2023	A01	41.7	NaN	0	20	49244	0	NaN	NaN	5	NaN

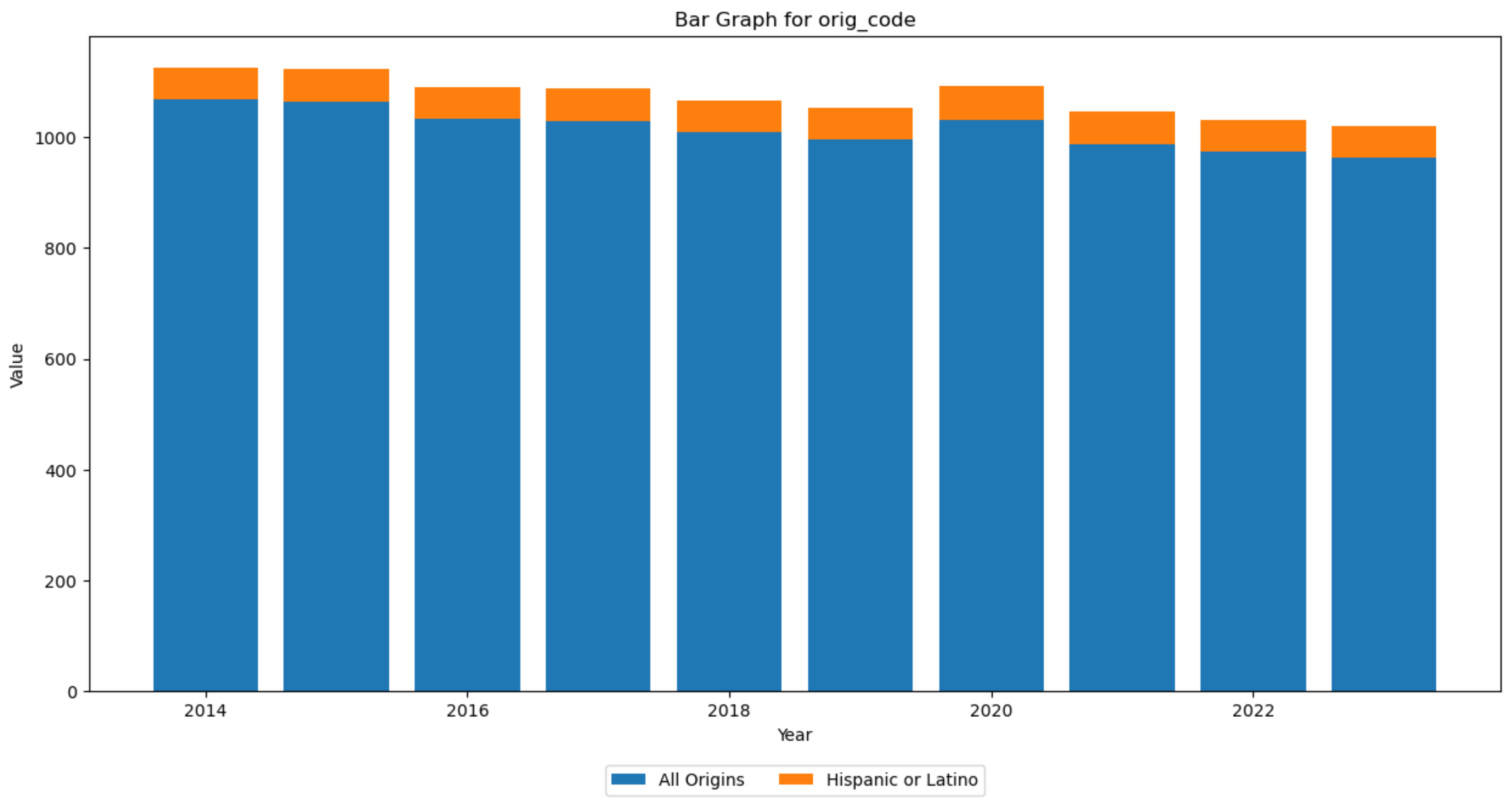
820 rows × 13 columns

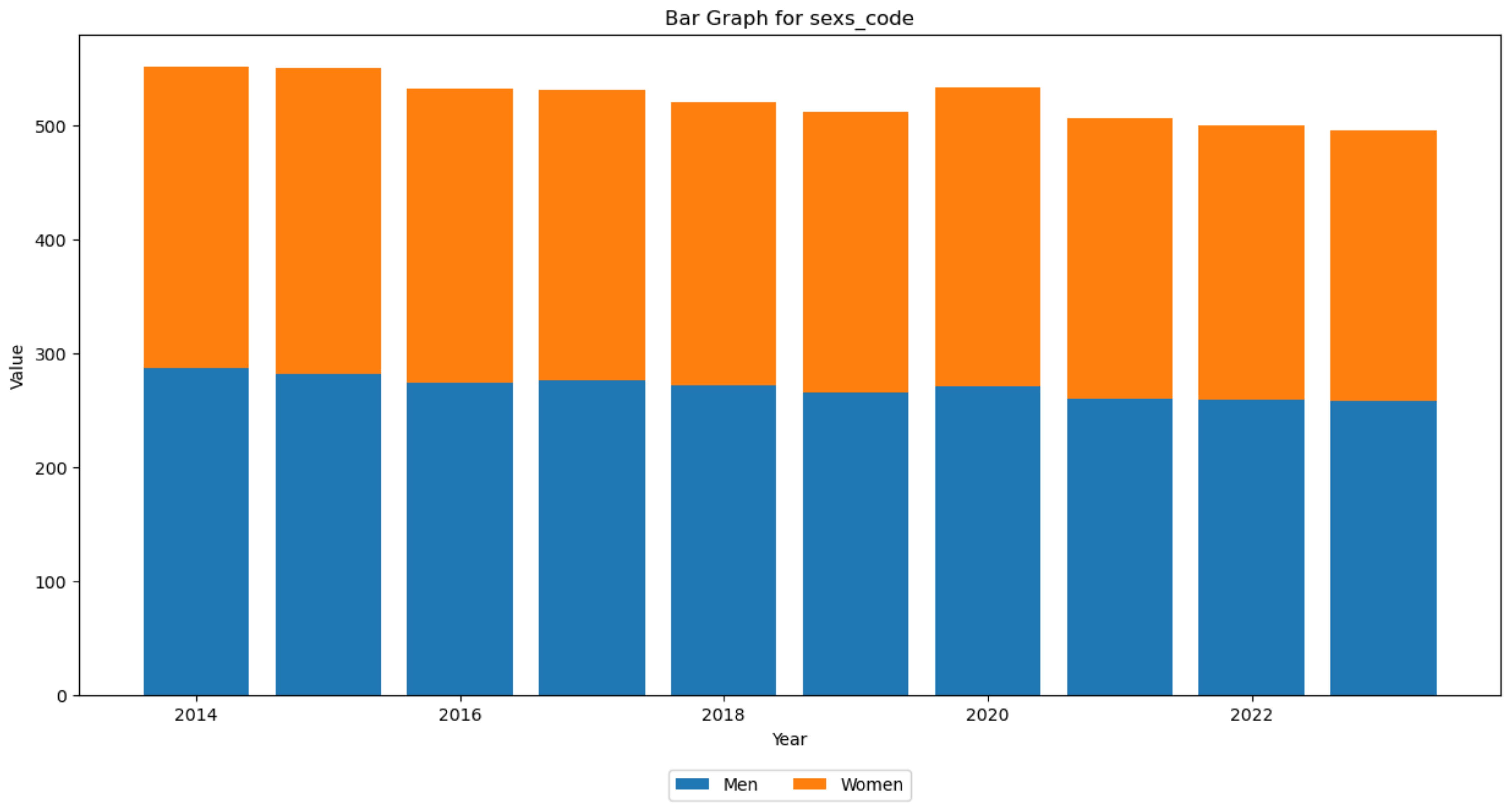
In [55]:
```
# list
list_dem = ['ages_code','race_code','orig_code','sexs_code']
```

In [56]:
```
#For loop for ever dem. in list
for dem in list_dem:
    #Figure size
    plt.figure(figsize=(15, 7))
    # Pivot the data
    pivot_df = dem_union.pivot_table(index='year', columns=dem, values='value', aggfunc='sum').fillna(0)

    # Iterate over each unique value in the demographic column to create stacked bars
    bottom_values = [0] * len(pivot_df.index)
   # For loop for each item on list_dem
    for category in pivot_df.columns:
        # Make bar plot
        plt.bar(pivot_df.index, pivot_df[category], bottom=bottom_values, label=one_dict.get(category, category))
        # Stack the values
        bottom_values += pivot_df[category]

    # x-label
    plt.xlabel('Year')
    # y-label
    plt.ylabel('Value')
    #title
    plt.title(f'Bar Graph for {dem}')

    # Add legend
    plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.1), fontsize=10, ncol=4)

    # Show the plot
    plt.show()
```


Bar Graph for ages_code
Value
Year
0
100
200
300
400
500
2014
2016
2018
2020
2022
16 to 24 years
25 years and over
25 to 34 years
35 to 44 years
45 to 54 years
55 to 64 years
65 years and over


Bar Graph for race_code
Value
Year
0
50
100
150
200
2014
2016
2018
2020
2022
Black or African American
Asian
White





Is union membership decreasing or increasing by industry?

```
In [57]: # look at values to find what is needed
         indy_code['indy_code'].unique()
```

```
Out[57]: array([   0,  168,  368,  369,  569,  770, 1068, 2467, 2468, 4067, 4068,
                4669, 6068, 6069, 6468, 6469, 6569, 6670, 6679, 6769, 6867, 6868,
                6869, 6990, 7069, 7268, 7269, 7569, 7858, 7859, 7968, 8558, 8559,
                8658, 8659, 8679, 8767, 8768, 9290])
```

```
In [58]: # indy list
         indy_df = dft_seq[
             (dft_seq['ages_code'] == 0) &
             (dft_seq['sexs_code'] == 0) &
             (dft_seq['race_code'] == 0) &
             (dft_seq['fips_code'] == 0) &
             (dft_seq['unin_code'] == 1) &
             (dft_seq['earn_code'] == 0) &
             (dft_seq['pcts_code'] == 0) &
             (dft_seq['indy_code'].isin([168, 369, 569, 770, 1068, 2468, 4068,
                4669, 6069, 6469, 6569, 6670, 6679, 6769, 6868,
                6869, 6990, 7069, 7269, 7569, 7859, 7968, 8559, 8659, 8679, 8768, 9290]))

         ]
```

```
In [59]: #Remove white space
         indy_df.rename(columns=lambda x: x.replace(' ', ''), inplace=True)
```

```
/var/folders/q9/wrynvqzj0dgb0yksnkbr0sj40000gn/T/ipykernel_9305/2806861879.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  indy_df.rename(columns=lambda x: x.replace(' ', ''), inplace=True)
```

In [60]:
```
# List of series that needs to be pulled
series_id_indy = indy_df['series_id'].unique().tolist()
# Remove spaces
series_id_indy = [x.replace(' ', '') for x in series_id_indy]
# List of year that needs to be pulled
year = list(range(2014,2024))
```

In [61]:
```
# look at list
series_id_indy
```

Out[61]:
```
['LUU0204794500',
 'LUU0204794700',
 'LUU0204794800',
 'LUU0204795000',
 'LUU0204795300',
 'LUU0204795400',
 'LUU0204795600',
 'LUU0204795700',
 'LUU0204795900',
 'LUU0204796000',
 'LUU0204796100',
 'LUU0204796300',
 'LUU0204796700',
 'LUU0204796800',
 'LUU0204796900',
 'LUU0204797000',
 'LUU0204797200',
 'LUU0204797300',
 'LUU0204797500',
 'LUU0204797600',
 'LUU0204797800',
 'LUU0204798000',
 'LUU0204798300',
 'LUU0204798400',
 'LUU0204921300',
 'LUU0204933400']
```

In [62]:
```
# Pull data that is only in series list
df_indy = all_df[all_df['series_id'].isin(series_id_indy) & all_df['year'].isin(year)]
```

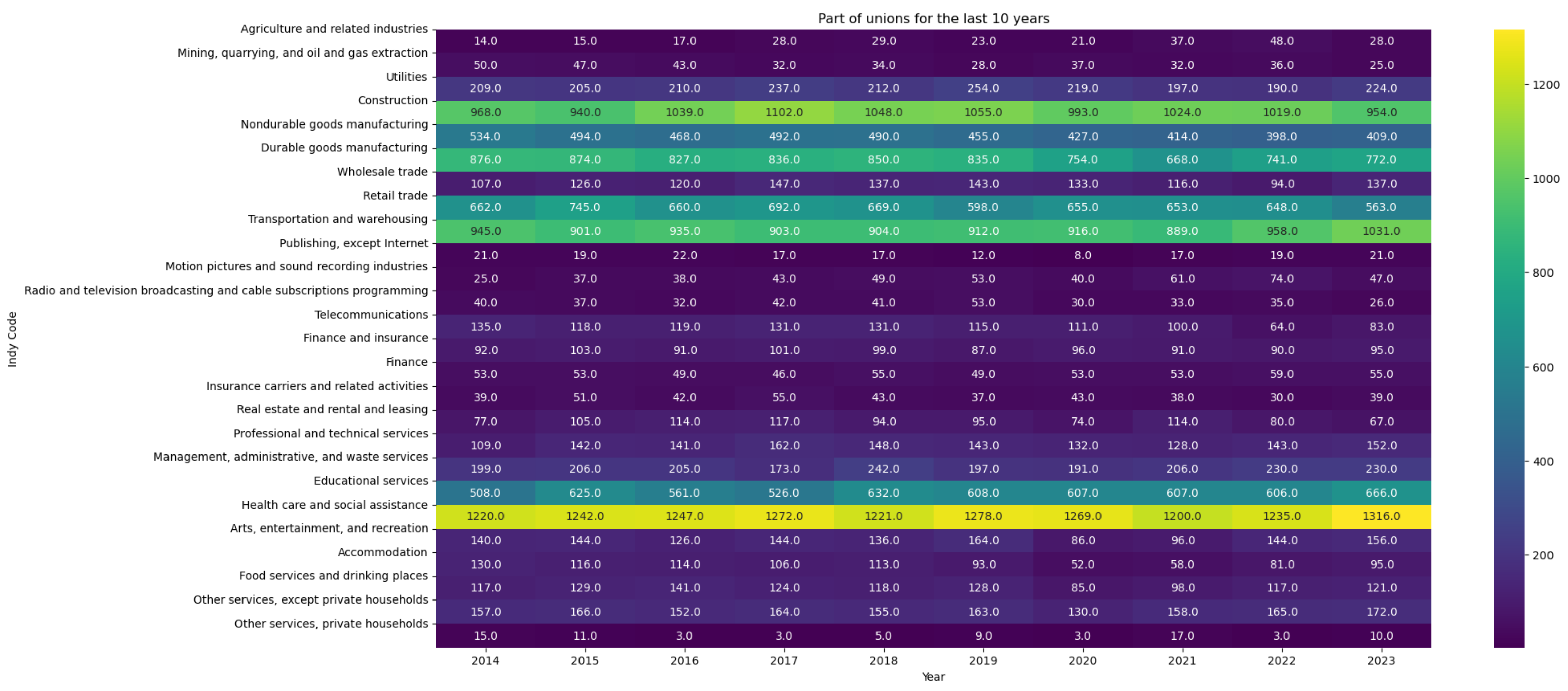
In [63]:
```
df_indy = df_indy.merge(indy_df[['series_id', 'indy_code', 'unin_code']], on='series_id', how='left', suffixes=('', '_indy'))
```

In [64]:
```
#check
df_indy.columns
```

Out[64]:
```
Index(['series_id', 'year', 'period', 'value', 'footnote_codes', 'stype',
       'lfst_code', 'seq_code', 'fips_code', 'indy_code', 'unin_code'],
      dtype='object')
```

In [65]:
```
# Create a mapping
indy_map = dict(zip(indy_code['indy_code'], indy_code['indy_text']))
```

In [66]:
```
# Groupby indy and year, calculate mean value
grouped_df = df_indy.groupby(['indy_code', 'year'])['value'].mean().reset_index()

# Pivot table for heatmap
pivot_table = grouped_df.pivot(index='indy_code', columns='year', values='value')

#Figure size
plt.figure(figsize=(20, 10))
# heatmap using sns
sns.heatmap(pivot_table, annot=True, fmt=".1f", cmap='viridis', cbar=True)

#x-label
plt.xlabel('Year')
#y-label
plt.ylabel('Indy Code')
#Title
plt.title('Part of unions for the last 10 years')

# Indy y-axis labels
plt.yticks(ticks=range(len(pivot_table.index)), labels=[indy_map.get(indy_code, indy_code) for indy_code in pivot_table.index])

# Display plot
plt.show()
```



The first plot shows the Median weekly earnings of full-time wages for the last ten years. Union members have been paid about $100 - 150 more than. However, the pay gap is slowly decreasing. The second graph shows that unions are more likely out west and north but less likely in the south. The third graph looks at the demographics of people in a union. There has not been much change in demographics over the last 10 years, but there was an increase in 2020. This could have to do with the fact that many people were overworking during this time, so they were more unhappy. Hispanics are less likely to be a part of a union. Younger individuals are less likely to be a part of unions. The fourth graph is a heat graph that shows the number of people in unions by industry. The top industries with the highest union numbers are: Health care and social assistance. Construction. Durable goods manufacturing, transportation, and warehousing.

- Data from bls.gov

Based on only union membership and individuals represented by unions,what would be the best place to open a new location in three years?

Remove any data that doe not meet publication criteria

In [67]:
```
# function to remove data that has footnote_code 7
def meets_criteria(data):
    return (data[data['footnote_codes'] != 7])
```

In [68]:
```
# Drop all rows from data that does not need criteria
df_earnings = meets_criteria(df_earnings)
merged_df = meets_criteria(merged_df)
dem_union = meets_criteria(dem_union)
df_indy = meets_criteria(df_indy)
```

In [69]:
```
df_earnings.head()
```

Out[69]:
```
              series_id  year  period  value  footnote_codes  stype  lfst_code  seq_code  fips_code
21993  LUU0253191200  2014     A01  763.0             NaN      0         25     31912         00
21994  LUU0253191200  2015     A01  776.0             NaN      0         25     31912         00
21995  LUU0253191200  2016     A01  801.0             NaN      0         25     31912         00
21996  LUU0253191200  2017     A01  829.0             NaN      0         25     31912         00
21997  LUU0253191200  2018     A01  861.0             NaN      0         25     31912         00
```

In [70]:
```
df_indy.head()
```

Out[70]:
```
       series_id  year  period  value  footnote_codes  stype  lfst_code  seq_code  fips_code  indy_code  unin_code
0  LUU0204794500  2014     A01   14.0             NaN      0         20     47945          0        168          1
1  LUU0204794500  2015     A01   15.0             NaN      0         20     47945          0        168          1
2  LUU0204794500  2016     A01   17.0             NaN      0         20     47945          0        168          1
3  LUU0204794500  2017     A01   28.0             NaN      0         20     47945          0        168          1
4  LUU0204794500  2018     A01   29.0             NaN      0         20     47945          0        168          1
```

In [71]:
```
dem_union.head()
```

Out[71]:
```
       series_id  year  period  value  footnote_codes  stype  lfst_code  seq_code  fips_code  ages_code  race_code  orig_code  sexs_code
0  LUU0204899600  2014     A01   11.1             NaN      0         20     48996          0        NaN        NaN          5        NaN
1  LUU0204899600  2015     A01   11.1             NaN      0         20     48996          0        NaN        NaN          5        NaN
2  LUU0204899600  2016     A01   10.7             NaN      0         20     48996          0        NaN        NaN          5        NaN
3  LUU0204899600  2017     A01   10.7             NaN      0         20     48996          0        NaN        NaN          5        NaN
4  LUU0204899600  2018     A01   10.5             NaN      0         20     48996          0        NaN        NaN          5        NaN
```

In [72]:
```
merged_df.head()
```

Out[72]:

	series_id	year	period	value	footnote_codes	stype	lfst_code	seq_code	fips_code	state_name	unin_code
0	LUU0204899601	2013	A01	10.7	NaN	0	20	48996	1	Alabama	1
1	LUU0204899601	2018	A01	9.2	NaN	0	20	48996	1	Alabama	1
2	LUU0204899601	2023	A01	7.5	NaN	0	20	48996	1	Alabama	1
3	LUU0204899602	2013	A01	23.1	NaN	0	20	48996	2	Alaska	1
4	LUU0204899602	2018	A01	18.5	NaN	0	20	48996	2	Alaska	1

In [73]:
```
df_earnings.head()
```

Out[73]:

	series_id	year	period	value	footnote_codes	stype	lfst_code	seq_code	fips_code
21993	LUU0253191200	2014	A01	763.0	NaN	0	25	31912	00
21994	LUU0253191200	2015	A01	776.0	NaN	0	25	31912	00
21995	LUU0253191200	2016	A01	801.0	NaN	0	25	31912	00
21996	LUU0253191200	2017	A01	829.0	NaN	0	25	31912	00
21997	LUU0253191200	2018	A01	861.0	NaN	0	25	31912	00

Code 7 in the footnote_codes column means the data does not meet the criteria to be published. Although the criteria is unknown, I decided that it would be best to remove it.

Combine datasets

I will combine all the data to simplify my assessment.

In [74]:
```
# Combine te datasets
data = pd.concat([df_earnings,merged_df,dem_union, df_indy], ignore_index=True)
```

In [75]:
```
data
```

Out[75]:

	series_id	year	period	value	footnote_codes	stype	lfst_code	seq_code	fips_code	state_name	unin_code	ages_code	race_code	orig_code	sexs_co
0	LUU0253191200	2014	A01	763.0	NaN	0	25	31912	00	NaN	NaN	NaN	NaN	NaN	N
1	LUU0253191200	2015	A01	776.0	NaN	0	25	31912	00	NaN	NaN	NaN	NaN	NaN	N
2	LUU0253191200	2016	A01	801.0	NaN	0	25	31912	00	NaN	NaN	NaN	NaN	NaN	N
3	LUU0253191200	2017	A01	829.0	NaN	0	25	31912	00	NaN	NaN	NaN	NaN	NaN	N
4	LUU0253191200	2018	A01	861.0	NaN	0	25	31912	00	NaN	NaN	NaN	NaN	NaN	N
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1421	LUU0204933400	2019	A01	128.0	NaN	0	20	49334	0	NaN	1.0	NaN	NaN	NaN	N
1422	LUU0204933400	2020	A01	85.0	NaN	0	20	49334	0	NaN	1.0	NaN	NaN	NaN	N
1423	LUU0204933400	2021	A01	98.0	NaN	0	20	49334	0	NaN	1.0	NaN	NaN	NaN	N
1424	LUU0204933400	2022	A01	117.0	NaN	0	20	49334	0	NaN	1.0	NaN	NaN	NaN	N
1425	LUU0204933400	2023	A01	121.0	NaN	0	20	49334	0	NaN	1.0	NaN	NaN	NaN	N

1426 rows × 16 columns

Remove unneeded columns

Not all columns are needed. I removed columns: footnotes, s_type, seq_code, lfst_code and period.

In [76]:
```
# Check to see if stype is needed.
print("Count of seasonally adjusted data in data:", data[data['stype']=='S']['stype'].count())
```

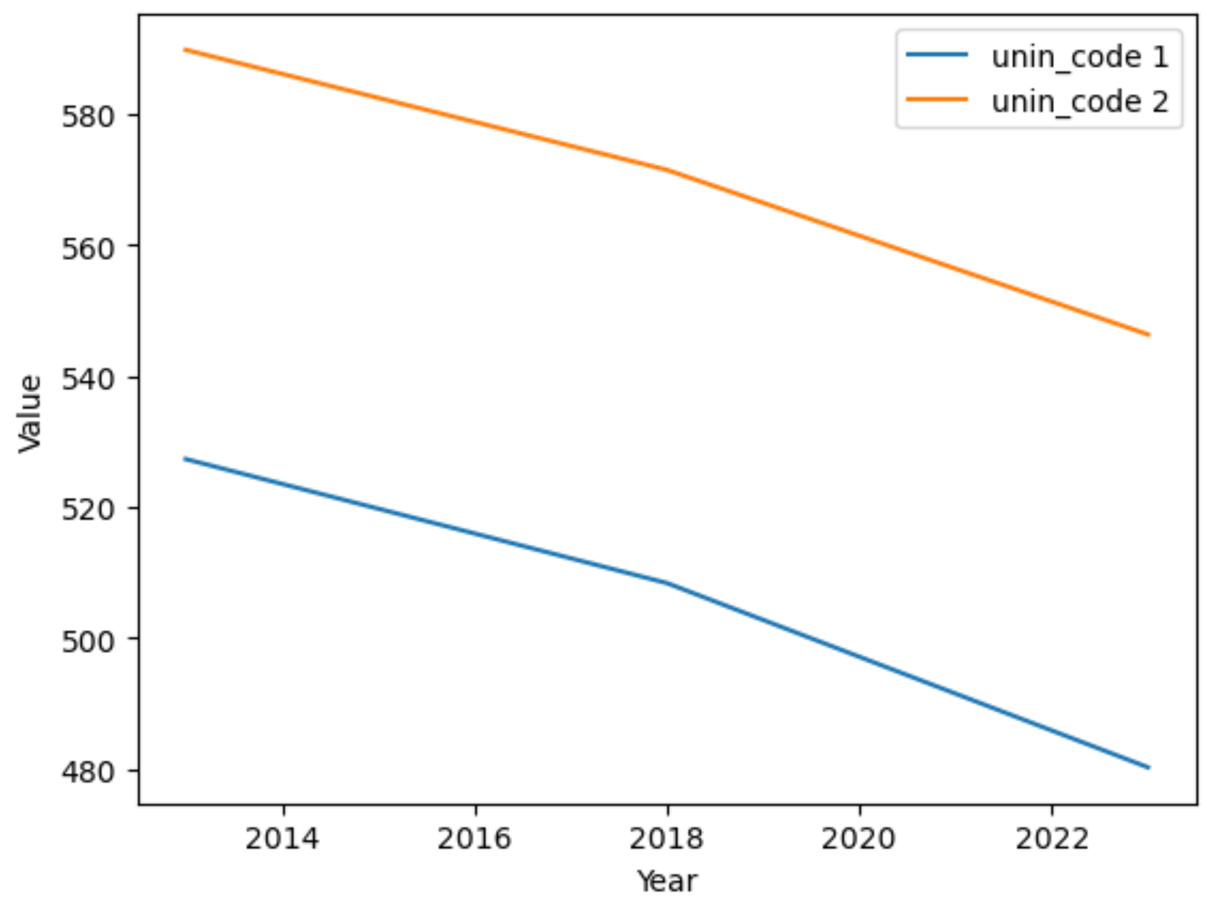
```
Count of seasonally adjusted data in data: 0
```

footnote_codes: Based on the footnote key, there are two different footnote codes: 5 and 7. 7 has already been removed. Footnote code 5 explains that agricultural data was excluded from the 1983-1999 data. However, this does not matter because the oldest data set is from 2014.
period: period will be removed because it has to do with quarterly data. I only downloaded the annual data, so this column only takes up space.
lfst_code: lfst_code says if they are full-time or part-time. For this assessment, it does not matter.
seq_code: seq_code will be removed because there is no key online. It is unknown what this code means.
stype: none of the data being reviewed has been seasonally adjusted; stype is not needed.

In [77]:
```
# drop list
drop_list = ['footnote_codes','period', 'lfst_code', 'seq_code', 'stype', 'fips_code']
stat_drop = ['footnote_codes','period', 'lfst_code', 'seq_code', 'stype']
```

In [78]:
```
# remove columns. Do it on all dataframes just incase only
df_earnings = df_earnings.drop(columns=drop_list)
merged_df = merged_df.drop(columns=stat_drop)
dem_union = dem_union.drop(columns=drop_list)
df_indy = df_indy.drop(columns=drop_list)
data = data.drop(columns=drop_list)
```

In [79]:
```
# Line Graph unions
for unin_code in merged_df["unin_code"].unique():
    subset = merged_df[merged_df['unin_code'] == unin_code]
    year_sum = subset.groupby('year')['value'].sum()
    plt.plot(year_sum.index, year_sum.values, label = f'unin_code {unin_code}')

plt.xlabel('Year')
plt.ylabel('Value')
plt.legend()
plt.show()
```



A lot of my cleaning was done in the first milestone when I made the initial graphs. My data was really clean. I plan on not looking for clean data in the next class because I need more experience cleaning data.

Question

Based on only union membership and individuals represented by unions,what would be the best place to open a new location in three years?

In [80]:
```
 # Notes to keep for this question:
  #- Unin_code = Code identifying union status
  #- state_name = Name of State
  #- fips_code = State Code
  #- Series_id = data for the Code identifying the specific series.
  #- value = % of people (union_code 1, 2, 3) by state

  #The series_id (LUU0202882000) can be broken out into:

#Code                   Value
#survey abbreviation=     LU
#seasonal (code)    =     U
#stype_code         =     0
#lfst_code          =     20
#seq_code           =    28820
#fips_code          =      00

# Notes: union code
unin_code
```
Out[80]:
```
2
```

In [81]:
```
# Data set with State and union membership
merged_df
```
Out[81]:

	series_id	year	value	fips_code	state_name	unin_code
0	LUU0204899601	2013	10.7	1	Alabama	1
1	LUU0204899601	2018	9.2	1	Alabama	1
2	LUU0204899601	2023	7.5	1	Alabama	1
3	LUU0204899602	2013	23.1	2	Alaska	1
4	LUU0204899602	2018	18.5	2	Alaska	1
...	...	...	...	...	...	...
301	LUU0204899755	2018	8.6	55	Wisconsin	2
302	LUU0204899755	2023	8.4	55	Wisconsin	2
303	LUU0204899756	2013	6.4	56	Wyoming	2
304	LUU0204899756	2018	7.7	56	Wyoming	2
305	LUU0204899756	2023	6.6	56	Wyoming	2

306 rows × 6 columns

Linear Regression with Categorical Encoding

In [82]:
```
# Import packages

#Test and train
from sklearn.model_selection import train_test_split, cross_val_score, cross_validate
# Linear Regression
from sklearn.linear_model import LinearRegression, Lasso, ElasticNet
# Random Forest Regressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
# GridSearch to check all three
from sklearn.model_selection import GridSearchCV
from sklearn.cluster import KMeans
# Gradient Boosting
from sklearn.ensemble import GradientBoostingRegressor
# ARIMA
from statsmodels.tsa.arima_model import ARIMA
# Lasso
# Accuracy
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import numpy as np
import itertools
```

In [83]:
```
# Column names
merged_df.columns
```

Out[83]:
```
Index(['series_id', 'year', 'value', 'fips_code', 'state_name', 'unin_code'], dtype='object')
```

In [84]:
```
# Look at year, state and union code
X = merged_df[['year', 'fips_code', 'unin_code']]
```

In [85]:
```
# Predict Y
y = merged_df['value']
```

In [86]:
```
# Make a train and test data
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=.2, random_state=42)
```

In [87]:
```
#Transform Data
# preprocessor transform columns
preprocessor = ColumnTransformer(
    transformers=[
        # Numerical columns
        ('num', StandardScaler(), ['year']),
        # Categorical columns
        ('cat', 'passthrough', ['fips_code', 'unin_code'])
    ])
```

In [88]:
```
# K_means
kmeans = KMeans(random_state=42)
```

In [89]:
```
models = {
    # Logistic Regession
    'Logistic_regression': {
        # Transform and process the model
        'model': Pipeline([
            ('preprocess', preprocessor),
            ('regress', LinearRegression())]),
        # Hyperparameters
        'params': {}
    },
    # Random forest
    'random_forest': {
        # Transform and process the model
        'model': Pipeline([
            ('preprocess', preprocessor),
            ('regress', RandomForestRegressor())]),
        # Hyperparameters
        'params':{'params': {
    'regress__n_estimators': [50, 100, 200],
    'regress__max_depth': [None, 10, 20],
    'regress__min_samples_split': [2, 5],
    'regress__min_samples_leaf': [1, 2],
    'regress__max_features': ['auto', 'sqrt'],
    'regress__bootstrap': [True, False]}}
    },
}
```

In [90]:
```
ElasticNet??
```

In [91]:
```
# Try three different models
for name, info in models.items():
    print(f'Running Grid Search for {name}')
    grid_search = GridSearchCV(info['model'], param_grid=info['params'], cv=10, verbose=0)
    grid_search.fit(X_train, y_train)
```

```
Running Grid Search for liner_regression
Running Grid Search for random_forest
Running Grid Search for gradient_boosting
```

In [92]:
```
# Find the best estimator
best_model = grid_search.best_estimator_
print(grid_search.best_estimator_)
print(grid_search.best_params_)
```

```
Pipeline(steps=[('preprocess',
                 ColumnTransformer(transformers=[('num', StandardScaler(),
                                                  ['year']),
                                                 ('cat', 'passthrough',
                                                  ['fips_code',
                                                   'unin_code'])])),
                ('regress',
                 GradientBoostingRegressor(learning_rate=0.5, max_depth=2,
                                           min_samples_leaf=2,
                                           n_estimators=1000))])
{'regress__learning_rate': 0.5, 'regress__max_depth': 2, 'regress__min_samples_leaf': 2, 'regress__n_estimators': 1000}
```

In [93]:
```
# Predict y
y_pred = best_model.predict(X_test)
```

In [94]:
```
# Accuracy test (metrics)
mse = mean_squared_error(y_test, y_pred)
mas = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)
```

In [95]:
```
# Print
print(f"Mean Absolute Error (MAE): {mas:.3f}")
print(f"Mean Squared Error (MSE): {mse:.3f}")
print(f"Root Mean Squared Error (RMSE): {rmse:.3f}")
print(f"R^2 Score: {r2:.3f}")
```

```
Mean Absolute Error (MAE): 0.935
Mean Squared Error (MSE): 1.512
Root Mean Squared Error (RMSE): 1.230
R^2 Score: 0.941
```

Results

Test 1 Pipeline(steps=[('preprocess', ColumnTransformer(transformers=[('num', StandardScaler(), ['year']), ('cat', 'passthrough', ['fips_code', 'unin_code'])])), ('regress', GradientBoostingRegressor())]) {'regress**learning_rate': 0.1, 'regress**n_estimators': 100}

Mean Absolute Error (MAE): 1.757 Mean Squared Error (MSE): 4.757 Root Mean Squared Error (RMSE): 2.181 R^2 Score: 0.815

Test 2 Pipeline(steps=[('preprocess', ColumnTransformer(transformers=[('num', StandardScaler(), ['year']), ('cat', 'passthrough', ['fips_code', 'unin_code'])])), ('regress', GradientBoostingRegressor(learning_rate=0.3, n_estimators=500))]) {'regress**learning_rate': 0.3, 'regress**n_estimators': 500}

Mean Absolute Error (MAE): 1.757 Mean Squared Error (MSE): 1.890 Root Mean Squared Error (RMSE): 1.375 R^2 Score: 0.926 **Test 3** Pipeline(steps=[('preprocess', ColumnTransformer(transformers=[('num', StandardScaler(), ['year']), ('cat', 'passthrough', ['fips_code', 'unin_code'])])), ('regress', GradientBoostingRegressor(n_estimators=1000))]) {'regress**learning_rate': 0.1, 'regress**n_estimators': 1000}

Mean Absolute Error (MAE): 1.757 Mean Squared Error (MSE): 1.567 Root Mean Squared Error (RMSE): 1.252 R^2 Score: 0.939 **Test 4** Pipeline(steps=[('preprocess', ColumnTransformer(transformers=[('num', StandardScaler(), ['year']), ('cat', 'passthrough', ['fips_code', 'unin_code'])])), ('regress', GradientBoostingRegressor(learning_rate=0.2, max_depth=2, min_samples_leaf=2, n_estimators=1000))]) {'regress**learning_rate': 0.2, 'regress**max_depth': 2, 'regress**min_samples_leaf': 2, 'regress**n_estimators': 1000} Mean Absolute Error (MAE): 1.757 Mean Squared Error (MSE): 1.541 Root Mean Squared Error (RMSE): 1.242 R^2 Score: 0.940

Test 5 - Best Test

Pipeline(steps=[('preprocess', ColumnTransformer(transformers=[('num', StandardScaler(), ['year']), ('cat', 'passthrough', ['fips_code', 'unin_code'])])), ('regress', GradientBoostingRegressor(learning_rate=0.5, max_depth=2, min_samples_leaf=2, n_estimators=1000))]) {'regresslearning_rate': 0.5, 'regressmax_depth': 2, 'regressmin_samples_leaf': 2, 'regressn_estimators': 1000} Mean Absolute Error (MAE): 0.935 Mean Squared Error (MSE): 1.512 Root Mean Squared Error (RMSE): 1.230 R^2 Score: 0.941

Test 6 Pipeline(steps=[('preprocess', ColumnTransformer(transformers=[('num', StandardScaler(), ['year']), ('cat', 'passthrough', ['fips_code', 'unin_code'])])), ('regress', GradientBoostingRegressor(learning_rate=0.2, max_depth=2, min_samples_leaf=2, n_estimators=1000, subsample=0.9))]) {'regress**learning_rate': 0.2, 'regress**max_depth': 2, 'regress**min_samples_leaf': 2, 'regress**n_estimators': 1000, 'regress__subsample': 0.9}

Mean Absolute Error (MAE): 1.757 Mean Squared Error (MSE): 1.597 Root Mean Squared Error (RMSE): 1.264 R^2 Score: 0.938 **Test 7** Pipeline(steps=[('preprocess', ColumnTransformer(transformers=[('num', StandardScaler(), ['year']), ('cat', 'passthrough', ['fips_code', 'unin_code'])])), ('regress', GradientBoostingRegressor(learning_rate=0.3, max_depth=2, min_samples_leaf=2, n_estimators=1000))]) {'regress**learning_rate': 0.3, 'regress**max_depth': 2, 'regress**min_samples_leaf': 2, 'regress**n_estimators': 1000}

Mean Absolute Error (MAE): 0.915 Mean Squared Error (MSE): 1.499 Root Mean Squared Error (RMSE): 1.224 R^2 Score: 0.942

Test 8 Running Grid Search for linear_regression Running Grid Search for random_forest Running Grid Search for gradient_boosting Running Grid Search for lasso Running Grid Search for elastic_net Running Grid Search for svr Pipeline(steps=[('preprocess', ColumnTransformer(transformers=[('num', StandardScaler(), ['year']), ('cat', 'passthrough', ['fips_code', 'unin_code'])])), ('regress', LinearRegression())]) {'regress**C': 10, 'regress**degree': 4, 'regress**epsilon': 1, 'regress**kernel': 'poly'} Mean Absolute Error (MAE): 4.178103049979377 Mean Squared Error (MSE): 25.5925273472311 Root Mean Squared Error (RMSE): 5.058905746031557 R^2 Score: 0.0024952896978454042

Test 9 Pipeline(steps=[('preprocess', ColumnTransformer(transformers=[('num', StandardScaler(), ['year']), ('cat', 'passthrough', ['fips_code', 'unin_code'])])), ('kmeans', KMeans(n_clusters=5, n_init=10, random_state=42)), ('regress', GradientBoostingRegressor(learning_rate=0.3, min_samples_leaf=2, random_state=42))]) {'kmeans**n_clusters': 5, 'regress**learning_rate': 0.3, 'regress**max_depth': 3, 'regress**min_samples_leaf': 2, 'regress__n_estimators': 100}

Mean Absolute Error (MAE): 1.422 Mean Squared Error (MSE): 3.103 Root Mean Squared Error (RMSE): 1.761 R^2 Score: 0.879

In [96]:
```
# Check for overfitting
cv_scores = cross_val_score(best_model, X_train, y_train, cv=10, scoring='neg_mean_squared_error')
```

In [97]:
```
# Check for overfitting or underfitting
cv = cross_validate(best_model, X, y, return_train_score=True)
```

In [98]:
```
# Extract and round the scores
train_scores = np.round(cv['train_score'], 3)
test_scores = np.round(cv['test_score'], 3)
```

In [99]:
```
# Calculate mean and standard deviation for both training and validation scores
train_mean = np.mean(train_scores)
train_std = np.std(train_scores)
test_mean = np.mean(test_scores)
test_std = np.std(test_scores)
```

In [100…
```
# Print score
print(f"Train Scores: {train_scores}")
print(f"Test Scores: {test_scores}")
# Print mean score
print(f"Mean Train Score: {train_mean:.3f}")
print(f"Mean Test Score: {test_mean:.3f}")
#Print standard deviation
print(f"Standard Deviation of Train Scores: {train_std:.3f}")
print(f"Standard Deviation of Test Scores: {test_std:.3f}")
```

```
Train Scores: [0.989 0.988 0.989 0.99  0.989]
Test Scores: [0.932 0.973 0.969 0.96  0.963]
Mean Train Score: 0.989
Mean Test Score: 0.959
Standard Deviation of Train Scores: 0.001
Standard Deviation of Test Scores: 0.014
```

In [101…
```
# List for 2028 data
fips_code_lt = dfs_fips['fips_code'].tolist()
unin_code_lt = [1,2]
```

In [102…
```
# Make a combinations of all options
combinations = list(itertools.product(fips_code_lt, unin_code_lt))
```

In [103…
```
# Make DataFrame
data_2028 = {
    'year': [2028] * len(combinations),
    'fips_code': [x[0] for x in combinations],
    'unin_code': [x[1] for x in combinations]}
```

In [104…
```
# Make data frame
df_2028 = pd.DataFrame(data_2028)
```

In [105…
```
df_2028
```

Out[105]:

	year	fips_code	unin_code
0	2028	0	1
1	2028	0	2
2	2028	1	1
3	2028	1	2
4	2028	2	1
...	...	...	...
99	2028	54	2
100	2028	55	1
101	2028	55	2
102	2028	56	1
103	2028	56	2

104 rows × 3 columns

In [106…
```
#Make the prediction
y_pred_2028 = best_model.predict(df_2028)
```

In [107…
```
# Add to table
df_2028['Prediction'] = y_pred_2028
```

In [108…
```
#year
year_28 = 2028
# Unique Code 2028
df_28_unique = df_2028['unin_code'].unique()
```

In [109…
```
# map names
df_2028['state_name'] = df_2028['fips_code'].map(state_name)
```

I ended up using three different models: linear regression, random forest, and gradient boosting. I also tried Lasso and ElasticNet, but my model kept overfitting, so I removed them.

Linear Regression

Based on the scikit-learn algorithm cheat sheet, my model has some category data, but the year data could be numeric, so I tried linear regression. I was trying to predict 2028. Although better than random forest, it could have been a better model.

Random Forest

I tried the classifier Random Forest because I used the union variable, which is labeled data, to help predict the values. This was the worst model.

Gradient Boosting

Gradient boosting was the best model by far. It was chosen every time except when I tried using Lasso and Elasticnet, but as I mentioned before, it caused my test data to be overfitted. In my last test, I tried adding k-means with gradient boosting because I had less than 10K rows of data, and my categories were known. Although the test was good, it was better without it.

Summary

Model prediction:

GradientBoostingRegressor:

- learning_rate: 0.5
- max_depth: 2
- min_samples_leaf: 2
- n_estimators: 1000

In [110…
```
# Print score
print(f"Train Scores: {train_scores}")
print(f"Test Scores: {test_scores}")
# Print mean score
print(f"Mean Train Score: {train_mean:.3f}")
print(f"Mean Test Score: {test_mean:.3f}")
#Print standard deviation
print(f"Standard Deviation of Train Scores: {train_std:.3f}")
print(f"Standard Deviation of Test Scores: {test_std:.3f}")
```

```
Train Scores: [0.989 0.988 0.989 0.99  0.989]
Test Scores: [0.932 0.973 0.969 0.96  0.963]
Mean Train Score: 0.989
Mean Test Score: 0.959
Standard Deviation of Train Scores: 0.001
Standard Deviation of Test Scores: 0.014
```

In [111…
```
# Print score
print(f"Differance Scores: {train_scores-test_scores}")
# Print mean score
print(f"Differance in Mean Score: {train_mean-test_mean:.3f}")
#Print standard deviation
print(f"Standard Deviation of Train Scores: {train_std-test_std:.3f}")
```

```
Differance Scores: [0.057 0.015 0.02  0.03  0.026]
Differance in Mean Score: 0.030
Standard Deviation of Train Scores: -0.014
```

I believe my model is a good predictor because there is a minimal deviation between the test and training data. The mean is high for the test and training data, which means my model fits the data very well. The standard deviation is also very low, meaning it is consistent and stable. The training and test scores are high, which means the data fits well. Although the training score is high, the test score is high, so it is not likely to be overfit.

Make a heat map

In [112…
```
df_2028
```

Out[112]:

	year	fips_code	unin_code	Prediction	state_name
0	2028	0	1	7.422533	U.S. Total
1	2028	0	2	8.549289	U.S. Total
2	2028	1	1	7.422533	Alabama
3	2028	1	2	8.549289	Alabama
4	2028	2	1	13.205583	Alaska
...	...	...	...	...	...
99	2028	54	2	9.640074	West Virginia
100	2028	55	1	7.202768	Wisconsin
101	2028	55	2	8.508881	Wisconsin
102	2028	56	1	5.423072	Wyoming
103	2028	56	2	6.791125	Wyoming

104 rows × 5 columns

In [113…
```
# Drop 0 from fips code
df_2028['fips_code'] = df_2028['fips_code'].drop(0)
```

In [114…
```
# Remove territories from us_map
territories_to_remove = ['78', '66', '69', '60', '72']
us_map = us_map[~us_map['STATEFP'].isin(territories_to_remove)]
```

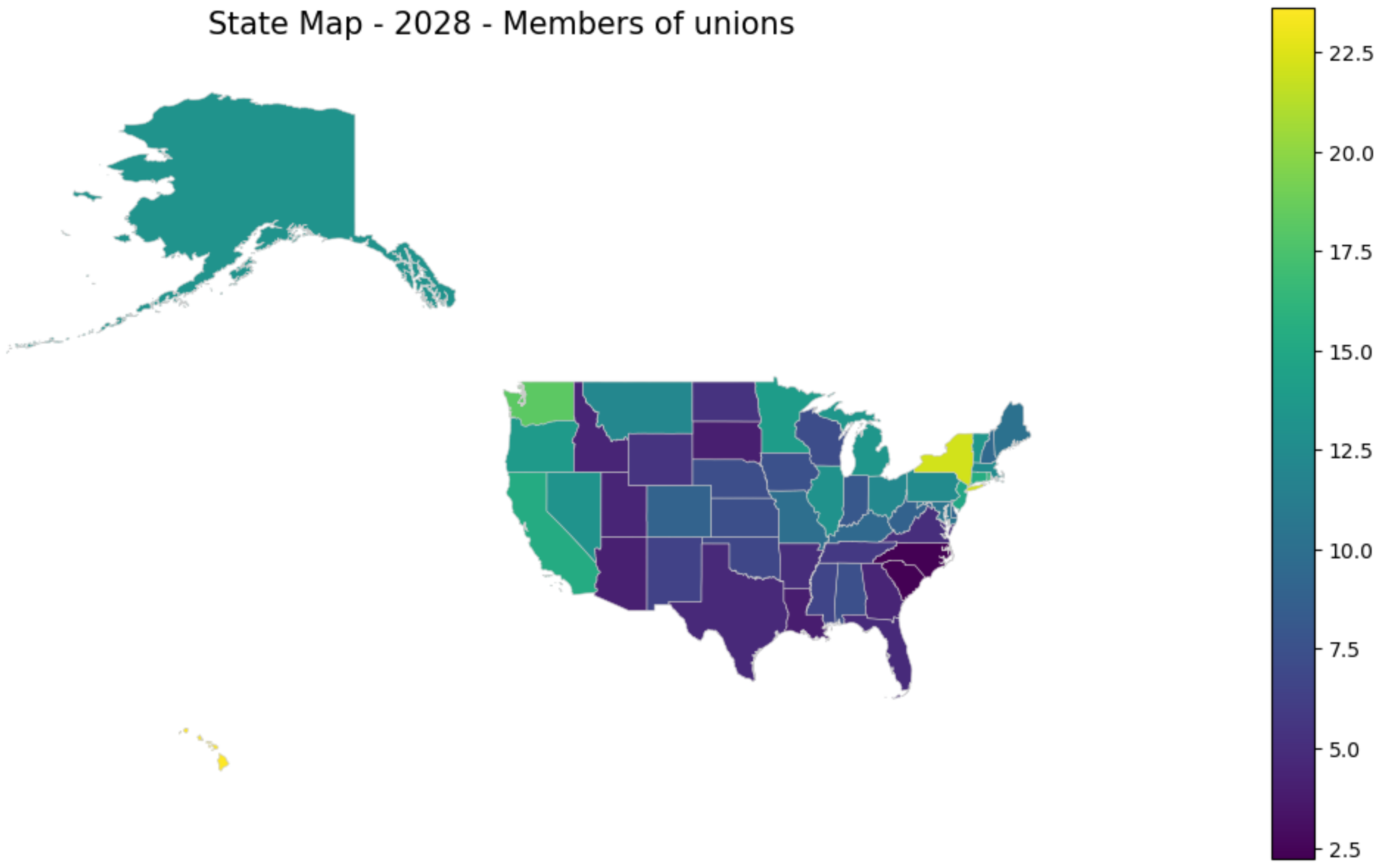
In [115…
```
# Merge us_map with state_union_merge based on 'fips' and 'fips_code'
us_states_merged_28 = pd.merge(us_map, df_2028, left_on='NAME', right_on='state_name', how='left')
```

In [116…
```
# Make a legder code
unicode_titles_map_28 = dict(zip(unin_code_28['unin_code'], unin_code_28['unin_text']))
```

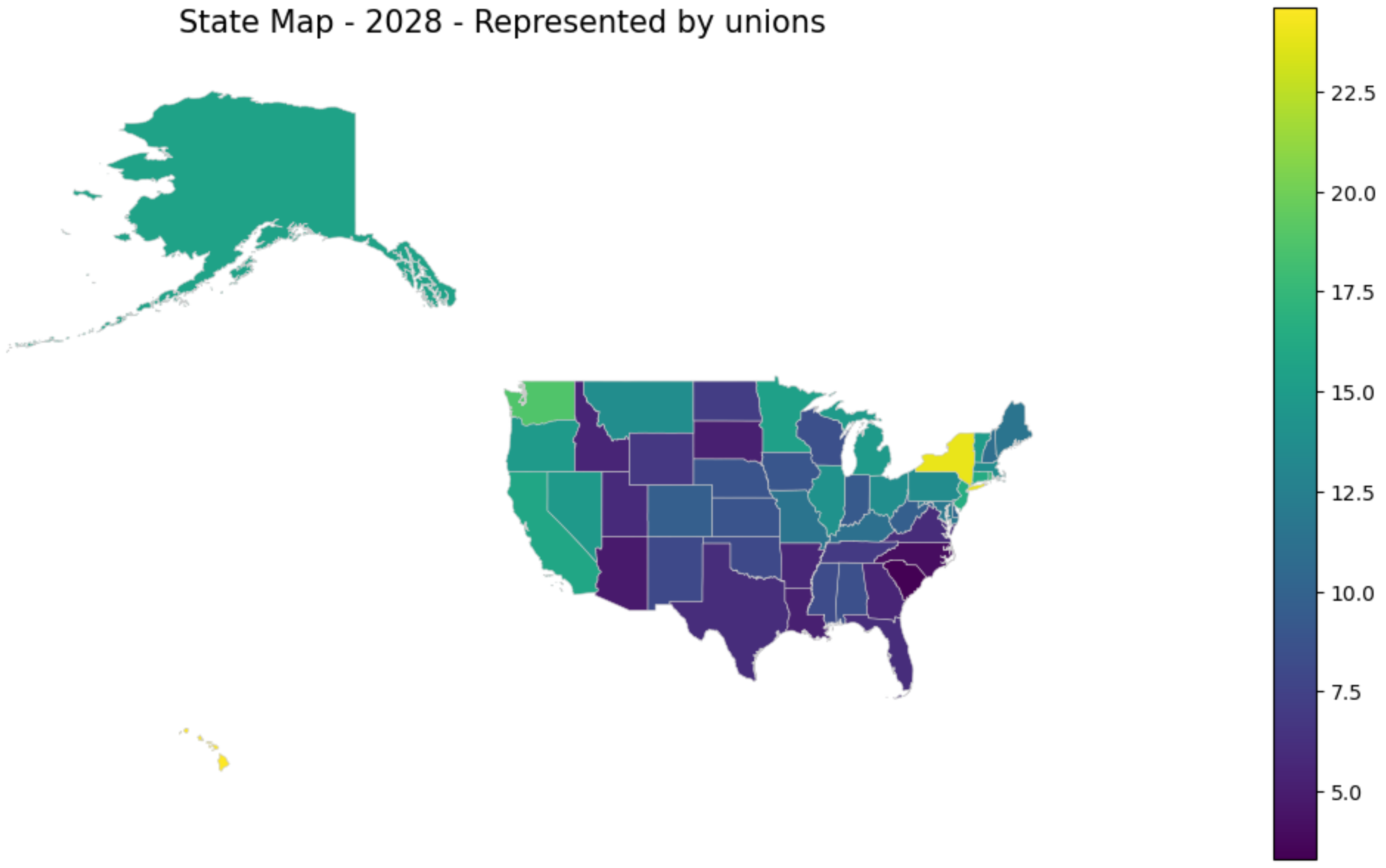
In [117…

```python
# for loop to plot people who are union and represented by a union on different maps
for code in us_states_merged_28['unin_code'].unique():
    # Filter the data for the current year and unique code
    year_data_28 = us_states_merged_28[(us_states_merged_28['year'] == 2028) & (us_states_merged_28['unin_code'] == code)]

    # Create the plot
    fig, ax = plt.subplots(figsize=(15, 15))
    year_data_28.plot(column='Prediction', cmap='viridis', linewidth=0.4, edgecolor='0.8', legend=True, legend_kwds={'shrink': 0.5}, ax=ax)

    # Set the title
    ax.set_title(f"State Map - {year_28} - {unicode_titles_map_28.get(code, 'Unknown Code')}", fontsize=15)

    # Set axis limits
    ax.set_xlim(-200, -50)
    ax.set_ylim(15, 75)

    # Remove axis
    ax.set_xticks([])
    ax.set_yticks([])
    ax.set_axis_off()

    # Show the plot
    plt.show()
```

State Map - 2028 - Members of unions



State Map - 2028 - Represented by unions


22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0