2021 AQI DATA

In [1]:
```
import pandas as pd
air_data= pd.read_csv('2021_aqi.csv')

air_data
```

Out[1]:

	date	zip_code	ReportingArea	StateCode	Latitude	Longitude	OZONEAQI
0	2021-01-01	2045	Weymouth	MA	42.2459	-70.9628	NaN
1	2021-01-02	2045	Weymouth	MA	42.2459	-70.9628	NaN
2	2021-01-03	2045	Weymouth	MA	42.2459	-70.9628	NaN
3	2021-01-04	2045	Weymouth	MA	42.2459	-70.9628	NaN
4	2021-01-05	2045	Weymouth	MA	42.2459	-70.9628	NaN
...	...	...	...	...	...	...	...
16395	2021-12-27	2446	Boston	MA	42.3510	-71.0510	13.0
16396	2021-12-28	2446	Boston	MA	42.3510	-71.0510	15.0
16397	2021-12-29	2446	Boston	MA	42.3510	-71.0510	12.0
16398	2021-12-30	2446	Boston	MA	42.3510	-71.0510	3.0
16399	2021-12-31	2446	Boston	MA	42.3510	-71.0510	6.0

16400 rows × 11 columns

In [2]:
```
air_data.groupby(['zip_code', 'Latitude', 'Longitude'])

air_data
```

Out[2]:

	date	zip_code	ReportingArea	StateCode	Latitude	Longitude	OZONEAQI
0	2021-01-01	2045	Weymouth	MA	42.2459	-70.9628	NaN
1	2021-01-02	2045	Weymouth	MA	42.2459	-70.9628	NaN
2	2021-01-03	2045	Weymouth	MA	42.2459	-70.9628	NaN
3	2021-01-04	2045	Weymouth	MA	42.2459	-70.9628	NaN
4	2021-01-05	2045	Weymouth	MA	42.2459	-70.9628	NaN
...	...	...	...	...	...	...	...
16395	2021-12-27	2446	Boston	MA	42.3510	-71.0510	13.0
16396	2021-12-28	2446	Boston	MA	42.3510	-71.0510	15.0
16397	2021-12-29	2446	Boston	MA	42.3510	-71.0510	12.0
16398	2021-12-30	2446	Boston	MA	42.3510	-71.0510	3.0
16399	2021-12-31	2446	Boston	MA	42.3510	-71.0510	6.0

16400 rows × 11 columns

In [3]:

```
unique_zip_codes = air_data['zip_code'].unique()
number_of_unique_zip_codes = len(unique_zip_codes)

print("Number of unique zip codes:", number_of_unique_zip_codes)
```

```
Number of unique zip codes: 45
```

In [4]:

```
## What is the overall AQI index for Boston based on 2021 AQI data?
from tabulate import tabulate

category = air_data['CategoryName'].value_counts()

category_df = pd.DataFrame({'CategoryName': category.index, 'Count': categor

table = tabulate(category_df, headers='keys', tablefmt='fancy_grid')
```

```
print(table)
```

	CategoryName	Count
0	Good	15699
1	Moderate	625
2	Unhealthy for Sensitive Groups	47

VISUALS FOR 2021 AQI DATA

Based on the 2021 AQI data, it appears that most of the zipcodes in Boston(15K out of 16K) had Good AQI levels meaning that overall quality of air in Boston is 'Good' The following visuals below depict the AQI in a consumable manner

In [5]:
```
## Get the mean PM2.5 AQI values per zip codes --> 45 total

grouped_data = air_data.groupby('zip_code')['PM2.5AQI'].mean().round(2).rese

grouped_data.head()
```

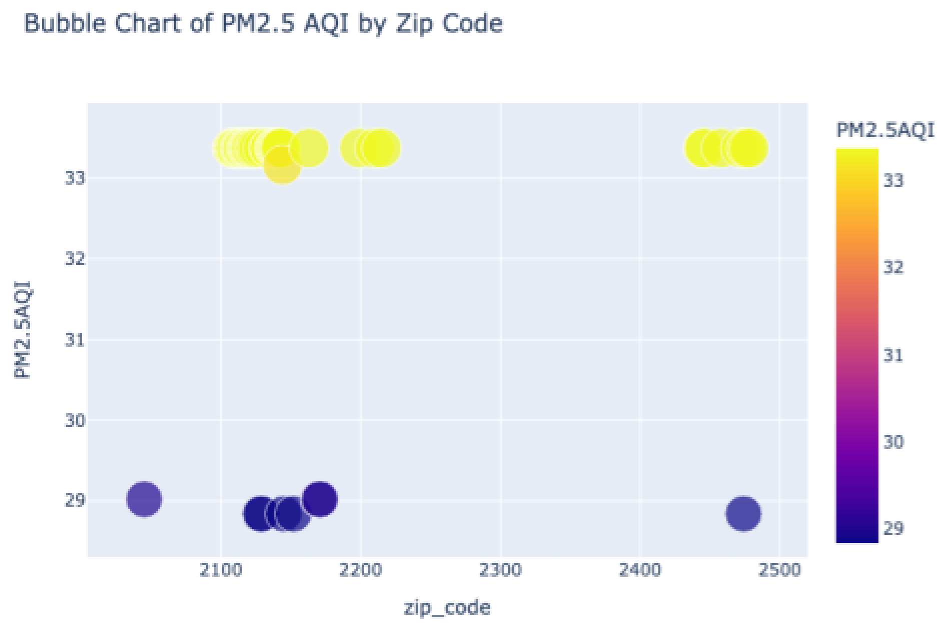
Out[5]:

	zip_code	PM2.5AQI
0	2045	29.02
1	2108	33.37
2	2109	33.37
3	2110	33.37
4	2111	33.37

In [6]:
```
### VISUAL 1: MAP DEPICTING CLUSTER OF AVERAGE AQI INDEX AROUND BOSTON AREA
import folium
from folium.plugins import MarkerCluster
from IPython.display import display


grouped_data = grouped_data.dropna(subset=['PM2.5AQI'])

boston_coords = [42.3601, -71.0589]  # Boston's latitude and longitude
m = folium.Map(location=boston_coords, zoom_start=12)


marker_cluster = MarkerCluster().add_to(m)


def get_marker_color(aqi):
    if aqi < 35:
        return 'green'
```

```
for index, row in grouped_data.iterrows():
    zip_code = row['zip_code']
    aqi = row['PM2.5AQI']
    color = get_marker_color(aqi)
    popup_text = f'<b>AQI:</b> {aqi}'
    folium.CircleMarker(location=boston_coords, radius= 20 , color=color, fi

# Create a legend for AQI values
legend_html = """
<div style="position: fixed; bottom: 50px; left: 50px; background-color: whi
    <p><strong>AQI Legend</strong></p>
    <p>AQI &lt; 35: Green (Good)</p>
</div>
"""


m.get_root().html.add_child(folium.Element(legend_html))

#display(m)

m.save("aqi_cluster_map.html")
```

In [7]:
```
import matplotlib.pyplot as plt
import plotly.express as px

# Assuming you already have 'grouped_data' containing the mean PM2.5 AQI for
# Filter out rows with NaN values in the 'PM2.5AQI' column
grouped_data = grouped_data.dropna(subset=['PM2.5AQI'])

fig = px.scatter(grouped_data, x='zip_code', y='PM2.5AQI', size='PM2.5AQI',

# Modify the layout to hide the legend and y-axis labels
fig.update_layout(showlegend=False)
fig.update_yaxes(visible=True)

# Save the chart as a PNG image
fig.write_image("bubble_chart.png")

# Now display the saved PNG image using matplotlib
img = plt.imread("bubble_chart.png")
plt.imshow(img)
plt.axis('off')  # Hide the axis
plt.show()
```



TRANSPORT DATA

Now that we have established the overall air quality to be 'Good' for 2021, we can explore transportation data by zipcodes to see how modes of transport can influence daily fluctations in air quality.

In [8]:
```
### cleaned census data for transportation ####

census_transport = pd.read_csv('census_transport.csv')

census_transport.head()
```

Out[8]:

	Zipcode	Estimated_Civilian_Noninstitutionalized_Population	Estimated_Civilian_Noni
0	2045	10120	
1	2108	4195	
2	2109	3508	
3	2110	2307	
4	2111	7841	

5 rows × 40 columns

In [9]:
```
### Total number of Boston residents across 45 zip codes transport mediums:
total_work = census_transport['Estimated_Total_Population_Commuting_to_Work_
total_work
```

Out[9]: 12630.631578947368

So this means, an avergae of 12.6K residents that are 16 years or older using some form to public transport to work on a daily basis

In [10]:
```
### Further exploring each of the modes of transportation##

car_carpool = census_transport['Percent_Total_Population_Commuting_to_Work_1
car = census_transport['Percent_Total_Population_Commuting_to_Work_16_years_

car_total = car_carpool + car
car_totals = car_total/2

car_totals
```

Out[10]: 17.43289473684211

Aprrox. 17% residents across the 45 zip codes in Boston area commute to work using a car(either driving alone or car pooling)

In [11]:
```
public_transport = census_transport['Percent_Total_Population_Commuting_to_W
public_transport
```

Out[11]: 23.46052631578947

Aprrox. 23% residents across the 45 zip codes in Boston area commute to work using a medium of public transport(train. commuter rail, bus, ferry)

In [12]:
```
### WALK #####
walked = census_transport['Percent_Total_Population_Commuting_to_Work_16_yea
walked
```

Out[12]: 22.376315789473686

Aprrox. 22% residents across the 45 zip codes in Boston area walk to their place of work(maybe close in proximity to place of work --> can be explored further)

In [13]:
```
### WORKED FROM HOME #####
home_work = census_transport['Percent_Total_Population_Commuting_to_Work_16_
home_work
```

Out[13]: 14.510526315789473

Aprrox. 15% residents across the 45 zip codes in Boston area work remotely and don't use any mode of transportation.

In [14]:
```
## TO SUMMARIZE: Across all 45 zip codes in Boston, 16+ years fall into the

other = census_transport['Percent_Total_Population_Commuting_to_Work_16_year
car_total = car_carpool + car
```

```
# Round the percentages to two decimal places
car_total = round(car_total, 2)
public_transport = round(public_transport, 2)
walked = round(walked, 2)
home_work = round(home_work, 2)
other = round(other, 2)

# Create a dictionary with the data
data = {
    'Means of Commuting': ['Car', 'Public Transport', 'Walk', 'Worked from H
    'Average Percentage': [car_total, public_transport, walked, home_work, c
}

# Create a DataFrame from the dictionary
commuting_df = pd.DataFrame(data)

# Convert the DataFrame to a tabular format
table = tabulate(commuting_df, headers='keys', tablefmt='fancy_grid')


print(table)
```

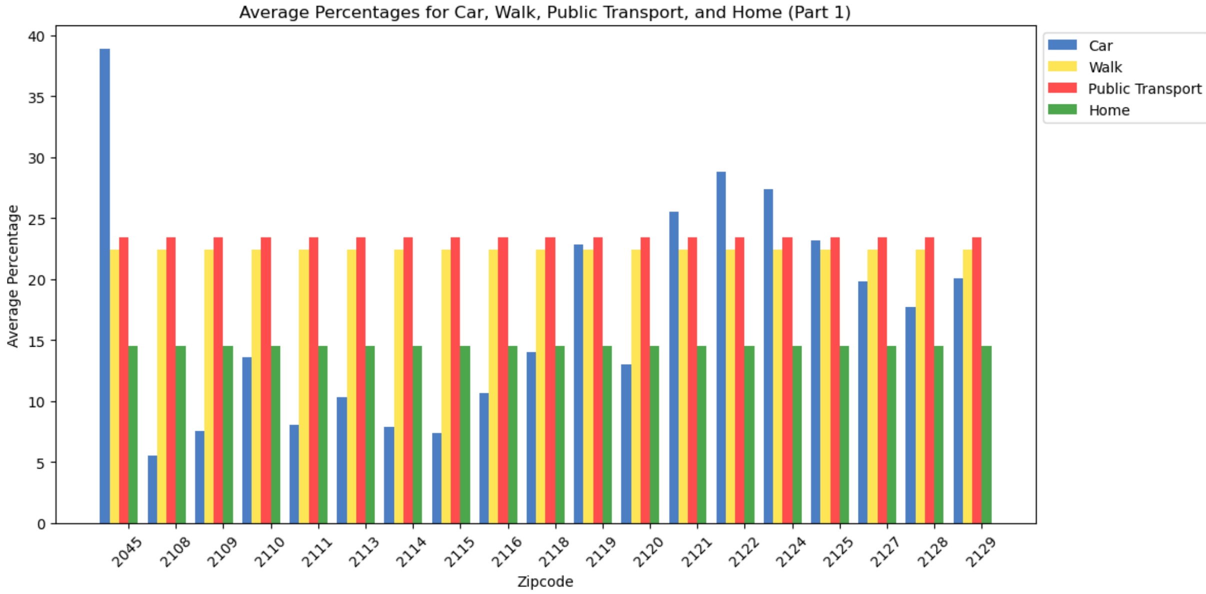
	Means of Commuting	Average Percentage
0	Car	34.87
1	Public Transport	23.46
2	Walk	22.38
3	Worked from Home	14.51
4	Other	4.77

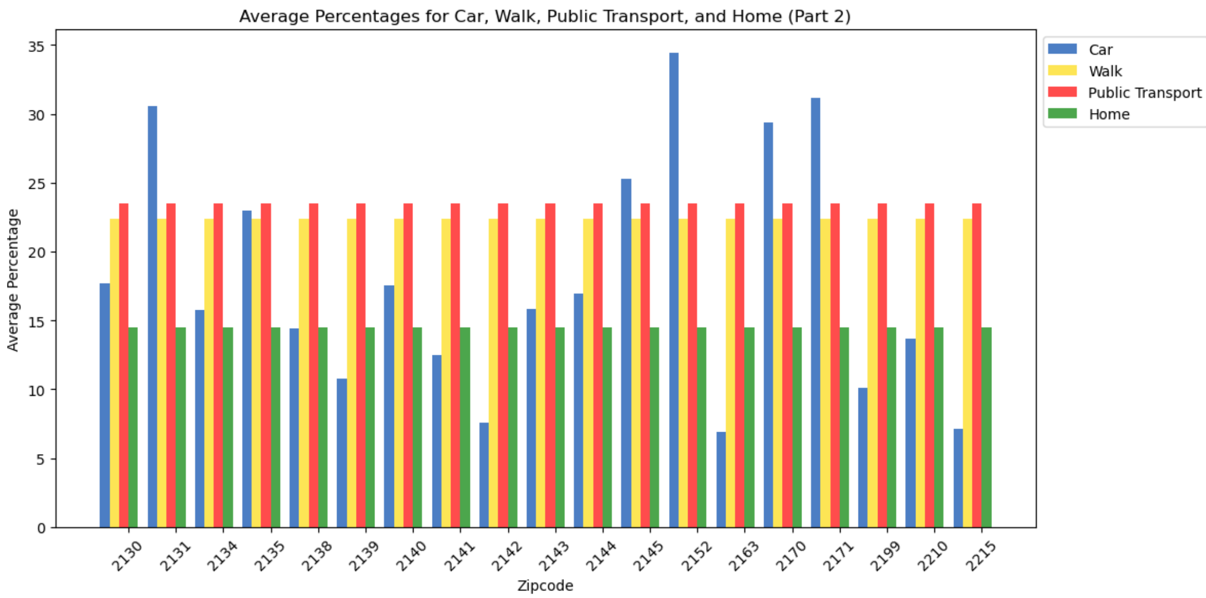
VISUALS FOR TRANSPORT DATA

Lets expand these overall trends to understand the most common mode of transport per zip code(note graph split into 2 parts for readablity):

In [15]:
```
import matplotlib.pyplot as plt
import numpy as np

# Calculate the average percentages for car, walk, public transport, and hom
census_transport['Average_Car'] = (census_transport['Percent_Total_Populatic
                                   census_transport['Percent_Total_Populatic
census_transport['Average_Walk'] = census_transport['Percent_Total_Populatic
census_transport['Average_Public_Transport'] = census_transport['Percent_Tot
census_transport['Average_Home'] = census_transport['Percent_Total_Populatic

# Create an array for x-positions
x = np.arange(len(census_transport['Zipcode']))

# Set the bar width
```

```
bar_width = 0.2

# Define the gap between zipcodes
gap = 0.2

# Define the number of zipcodes to split into two graphs (e.g., half the zip
split_index = len(x) // 2


custom_colors = ['#0047AB', '#FDDA0D', 'red', 'green']


# Create the first grouped bar chart
plt.figure(figsize=(12, 6))
car_bars = plt.bar(x[:split_index] - 1.5 * bar_width - gap, census_transport
walk_bars = plt.bar(x[:split_index] - 0.5 * bar_width - gap, census_transpor
pt_bars = plt.bar(x[:split_index] + 0.5 * bar_width - gap, census_transport[
home_bars = plt.bar(x[:split_index] + 1.5 * bar_width - gap, census_transpor

plt.xlabel('Zipcode')
plt.ylabel('Average Percentage')
plt.title('Average Percentages for Car, Walk, Public Transport, and Home (Pa

# Adjust the x-axis ticks and labels
plt.xticks(x[:split_index], census_transport['Zipcode'][:split_index], rotat

# Place the legend outside the graph
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))

plt.tight_layout()
plt.show()

# Create the second grouped bar chart
plt.figure(figsize=(12, 6))
car_bars = plt.bar(x[split_index:] - 1.5 * bar_width - gap, census_transport
walk_bars = plt.bar(x[split_index:] - 0.5 * bar_width - gap, census_transpor
pt_bars = plt.bar(x[split_index:] + 0.5 * bar_width - gap, census_transport[
home_bars = plt.bar(x[split_index:] + 1.5 * bar_width - gap, census_transpor

plt.xlabel('Zipcode')
plt.ylabel('Average Percentage')
plt.title('Average Percentages for Car, Walk, Public Transport, and Home (Pa

# Adjust the x-axis ticks and labels
plt.xticks(x[split_index:], census_transport['Zipcode'][split_index:], rotat

# Place the legend outside the graph
plt.legend(loc='upper left', bbox_to_anchor=(1, 1))

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





Based on the grouped bar graphs above, we see that Car seems to be the most popular medium of transport, followed by public transport. What can be further studied is the impact this can have on air quality and how Boston combats this since the air quality for 3032 is relatively 'Good'

PPI DATA

Next, lets explore PPI Data Trends to measure how proximity to roads impact residents of Boston, especially different racial groups disproportionately.

In [16]:
```
ppi_df  = pd.read_csv('ppi.csv')

ppi_df
```

Out[16]:

	objectid	g250m_id	commtypid	commtype	nhwhi_10	nhaa_10	nhapi_10	lat
0	1	144054.0	3	Maturing Suburbs	26.88	0.37	3.03	(
1	2	115030.0	3	Maturing Suburbs	33.00	0.00	14.59	
2	3	232476.0	4	Developing Suburbs	2.66	0.00	0.00	(
3	4	112471.0	4	Developing Suburbs	1.34	0.00	0.04	(
4	5	148255.0	1	Inner Core	0.00	0.00	0.00	(
...	...	...	...	...	...	...	...	
62171	62172	70856.0	3	Maturing Suburbs	3.25	0.00	0.00	(
62172	62173	85868.0	3	Maturing Suburbs	0.00	0.00	0.00	(
62173	62174	73413.0	2	Regional Urban Centers	107.08	1.19	3.08	
62174	62175	88437.0	3	Maturing Suburbs	4.23	0.00	0.17	(
62175	62176	25705.0	4	Developing Suburbs	57.66	0.05	1.02	

62176 rows × 11 columns

In [17]:

```
### PPI Average Densities for Category 0

ppi_df.dropna(inplace=True)
ppi_df0 = ppi_df[ppi_df['ppi5'] == 0]
ppi_df0_avg = ppi_df0[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
ppi_df0_std = ppi_df0[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
print(ppi_df0_avg.head())
```

```
nhwhi_10    12.783550
nhaa_10      0.516185
nhapi_10     0.780224
lat_10       0.507531
nhoth_10     0.289226
dtype: float64
```

In [18]:

```
### PPI Average Densities for Category 1
ppi_df1 = ppi_df[ppi_df['ppi5'] == 1]
ppi_df1_avg = ppi_df1[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
ppi_df1_std = ppi_df1[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
print(ppi_df1_avg.head())
```

```
nhwhi_10    24.379456
nhaa_10      1.080559
nhapi_10     1.518334
lat_10       1.197523
nhoth_10     0.612091
dtype: float64
```

In [19]:

```
### PPI Average Densities for Category 2
ppi_df2 = ppi_df[ppi_df['ppi5'] == 2]
ppi_df2_avg = ppi_df2[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
ppi_df2_std = ppi_df2[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
print(ppi_df2_avg.head())
```

```
nhwhi_10    34.607915
nhaa_10      2.041301
nhapi_10     2.345419
lat_10       1.854871
nhoth_10     0.950391
dtype: float64
```

In [20]:

```
### PPI Average Densities for Category 3
ppi_df3 = ppi_df[ppi_df['ppi5'] == 3]
ppi_df3_avg = ppi_df3[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
ppi_df3_std = ppi_df3[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
print(ppi_df3_avg.head())
```

```
nhwhi_10    46.888427
nhaa_10      3.960835
nhapi_10     3.413472
lat_10       3.451681
nhoth_10     1.699663
dtype: float64
```

In [21]:

```
### PPI Average Densities for Category 4
ppi_df4 = ppi_df[ppi_df['ppi5'] == 4]
ppi_df4_avg = ppi_df4[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
ppi_df4_std = ppi_df4[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
print(ppi_df4_avg.head())
```

```
nhwhi_10    72.887019
nhaa_10      9.893672
nhapi_10     7.263983
lat_10       9.668967
nhoth_10     3.697175
dtype: float64
```

In [22]:

```
### PPI Average Densities for Category 5
ppi_df5 = ppi_df[ppi_df['ppi5'] == 5]
ppi_df5_avg = ppi_df5[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
ppi_df5_std = ppi_df5[['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_1
print(ppi_df5_avg.head())
```

```
nhwhi_10    89.178365
nhaa_10     15.449001
nhapi_10    15.333186
lat_10      21.452750
nhoth_10     5.590272
dtype: float64
```

VISUALS FOR PPI DATA

Next Steps:

1. Have census data that contains details about household sizes, and average income. Need to conduct EDA
2. Now that the basic trends have been established, what can be concluded about the yearly changes in Boston's AQI and the health impacts?

In [23]:
```
ppi_new = ppi_df['ppi5'].value_counts()
#ppi_new = ppi_new.sort_values(ascending=True)
ppi = sum(ppi_new)
ppi
```

Out[23]:
```
62176
```

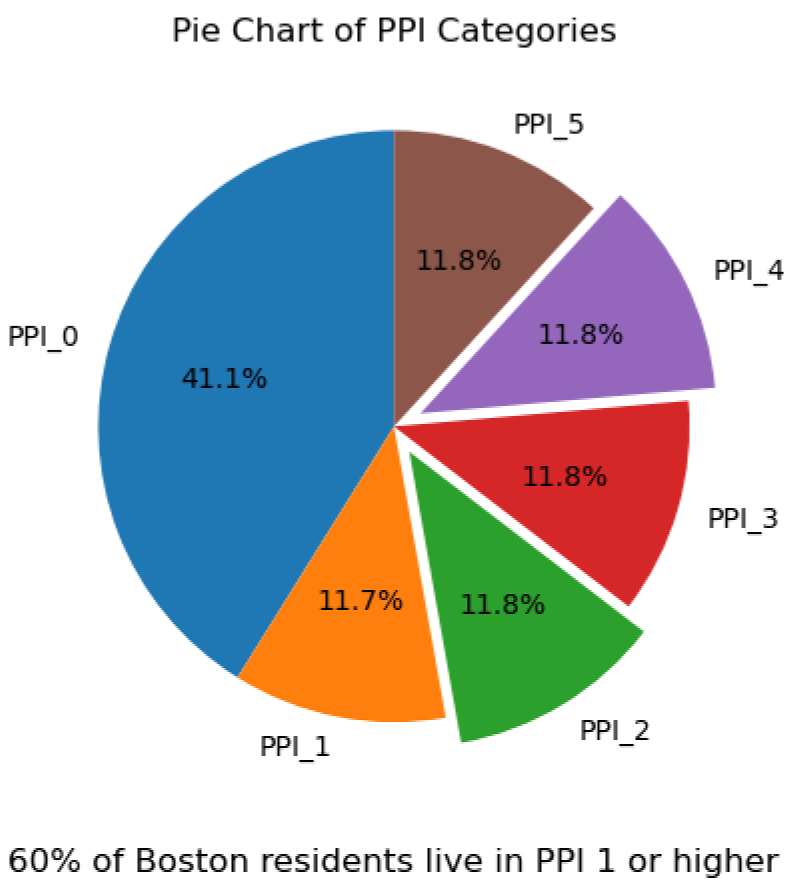
In [24]:
```
ppi_new
```

Out[24]:
```
0    25571
5     7342
4     7340
3     7335
2     7326
1     7262
Name: ppi5, dtype: int64
```

In [25]:
```
ppi0 = 25571/ppi

pp11=7262/ppi

ppi2 = 7326/ppi

ppi3 = 7335/ppi

ppi4 = 7340/ppi

ppi5 = 7342/ppi
```

In [26]:
```
import matplotlib.pyplot as plt

x = [25571, 7262, 7326, 7335, 7340, 7342]
labels = ['PPI_0', 'PPI_1', 'PPI_2', 'PPI_3', 'PPI_4', 'PPI_5']
explode = (0, 0, 0.1, 0, 0.1, 0)

# Create a pie chart with percentages displayed inside each slice
```

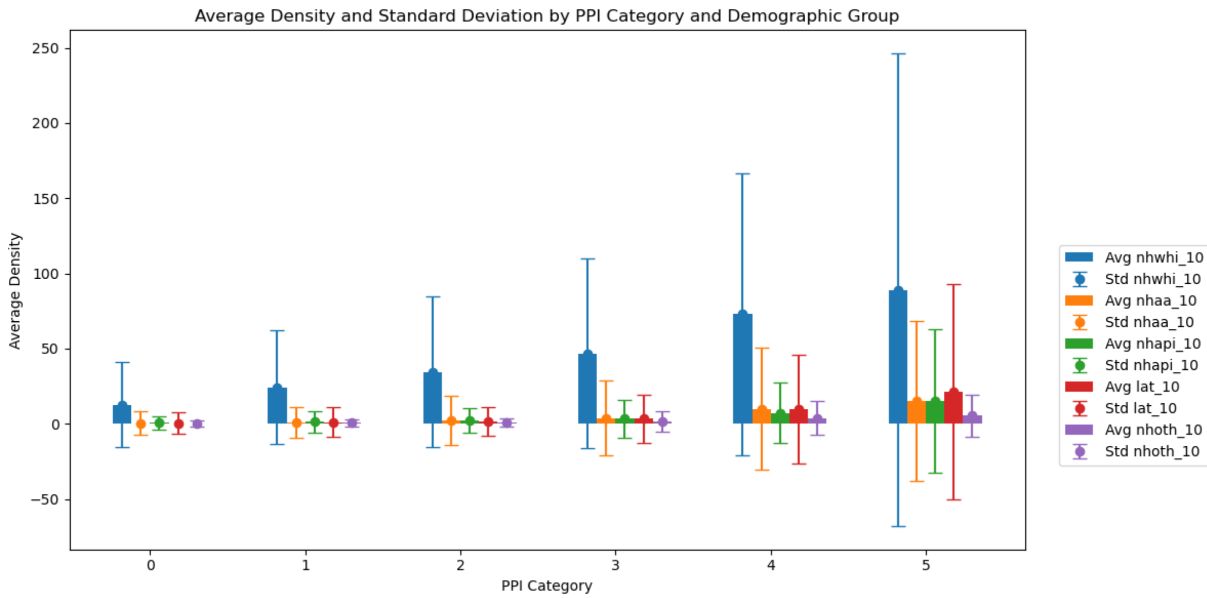
```
plt.pie(x, labels=labels, explode=explode, autopct='%1.1f%%', startangle=90)

# Add a title
plt.title('Pie Chart of PPI Categories')

# Add a label
plt.text(0, -1.5, '60% of Boston residents live in PPI 1 or higher', ha='cer

plt.show()
```



Version 1 and 2 for PPI and RACIAL GROUPS

In [27]:
```
import matplotlib.pyplot as plt

# Define demographic groups
demographic_groups = ['nhwhi_10', 'nhaa_10', 'nhapi_10', 'lat_10', 'nhoth_10

# Data for each 'ppi5' category
ppi_categories = ['0', '1', '2', '3', '4', '5']
ppi_avgs = [ppi_df0_avg, ppi_df1_avg, ppi_df2_avg, ppi_df3_avg, ppi_df4_avg,
ppi_stds = [ppi_df0_std, ppi_df1_std, ppi_df2_std, ppi_df3_std, ppi_df4_std,

# Create a bar chart for each demographic group
fig, ax = plt.subplots(figsize=(12, 6))
width = 0.12 # Width of each bar

for i, group in enumerate(demographic_groups):
    avg_values = [avg[group] for avg in ppi_avgs]
```

```
    std_values = [std[group] for std in ppi_stds]

    x = [j + i * width for j in range(len(ppi_categories))]
    plt.bar(x, avg_values, width=width, label=f'Avg {group}')
    plt.errorbar(x, avg_values, yerr=std_values, fmt='o', label=f'Std {group

plt.xlabel('PPI Category')
plt.ylabel('Average Density')
plt.title('Average Density and Standard Deviation by PPI Category and Demogr
plt.xticks([i + 1.5 * width for i in range(len(ppi_categories))], ppi_catego
plt.legend(loc='upper right', bbox_to_anchor=(1.2, 0.6))
plt.tight_layout()
plt.show()
```



CENSUS DATA

In [28]:

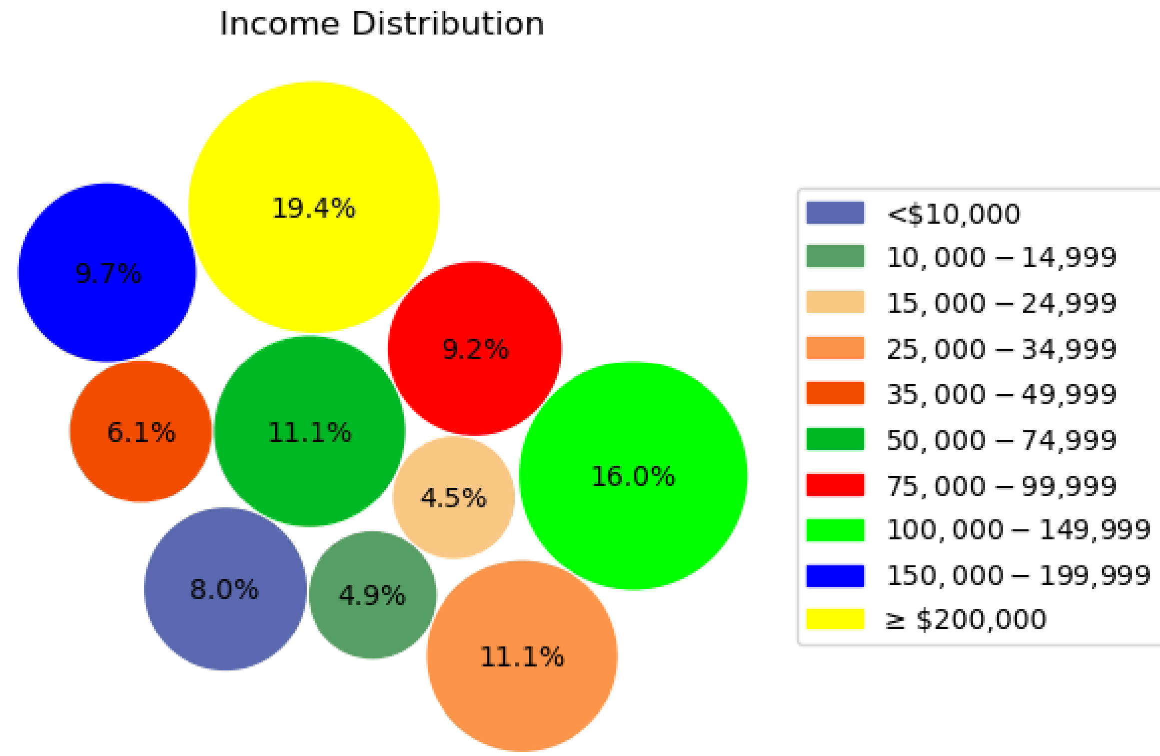
```
import pandas as pd

# Specify the income range categories

first= census_transport['Percent_Total_Households_Income_and_Benefits_Less t

second= census_transport['Percent_Total_Households_Income_and_Benefits_$10,0

third=  census_transport['Percent_Total_Households_Income_and_Benefits_$25,0

fourth=  census_transport['Percent_Total_Households_Income_and_Benefits_$50,

fifth=  census_transport['Percent_Total_Households_Income_and_Benefits_$35,0

sixth=  census_transport['Percent_Total_Households_Income_and_Benefits_$50,0

seventh=  census_transport['Percent_Total_Households_Income_and_Benefits_$75

eight= census_transport['Percent_Total_Households_Income_and_Benefits_$100,0
```

```
nine= census_transport['Percent_Total_Households_Income_and_Benefits_$150,00

ten= census_transport['Percent_Total_Households_Income_and_Benefits_$200,000
```

In [29]:
```
import matplotlib.pyplot as plt
import numpy as np

class BubbleChart:
    def __init__(self, income_means, bubble_spacing=0):
        """
        Setup for bubble collapse.

        Parameters
        ----------
        income_means : array-like
            Mean income values for different categories.
        bubble_spacing : float, default: 0
            Minimal spacing between bubbles after collapsing.
        """
        income_means = np.asarray(income_means)
        r = np.sqrt(income_means / np.pi)

        self.bubble_spacing = bubble_spacing
        self.bubbles = np.ones((len(income_means), 4))
        self.bubbles[:, 2] = r
        self.bubbles[:, 3] = income_means
        self.maxstep = 2 * self.bubbles[:, 2].max() + self.bubble_spacing
        self.step_dist = self.maxstep / 2

        # calculate initial grid layout for bubbles
        length = np.ceil(np.sqrt(len(self.bubbles)))
        grid = np.arange(length) * self.maxstep
        gx, gy = np.meshgrid(grid, grid)
        self.bubbles[:, 0] = gx.flatten()[:len(self.bubbles)]
        self.bubbles[:, 1] = gy.flatten()[:len(self.bubbles)]

        self.com = self.center_of_mass()

    def center_of_mass(self):
        return np.average(
            self.bubbles[:, :2], axis=0, weights=self.bubbles[:, 3]
        )

    def center_distance(self, bubble, bubbles):
        return np.hypot(bubble[0] - bubbles[:, 0],
                        bubble[1] - bubbles[:, 1])

    def outline_distance(self, bubble, bubbles):
        center_distance = self.center_distance(bubble, bubbles)
        return center_distance - bubble[2] - \
            bubbles[:, 2] - self.bubble_spacing

    def check_collisions(self, bubble, bubbles):
        distance = self.outline_distance(bubble, bubbles)
        return len(distance[distance < 0])
```

```
    def collides_with(self, bubble, bubbles):
        distance = self.outline_distance(bubble, bubbles)
        return np.argmin(distance, keepdims=True)

    def collapse(self, n_iterations=50):
        """
        Move bubbles to the center of mass.

        Parameters
        ----------
        n_iterations : int, default: 50
            Number of moves to perform.
        """
        for _ in range(n_iterations):
            moves = 0
            for i in range(len(self.bubbles)):
                rest_bub = np.delete(self.bubbles, i, 0)
                # try to move directly towards the center of mass
                # direction vector from bubble to the center of mass
                dir_vec = self.com - self.bubbles[i, :2]

                # shorten direction vector to have length of 1
                dir_vec = dir_vec / np.sqrt(dir_vec.dot(dir_vec))

                # calculate new bubble position
                new_point = self.bubbles[i, :2] + dir_vec * self.step_dist
                new_bubble = np.append(new_point, self.bubbles[i, 2:4])

                # check whether new bubble collides with other bubbles
                if not self.check_collisions(new_bubble, rest_bub):
                    self.bubbles[i, :] = new_bubble
                    self.com = self.center_of_mass()
                    moves += 1
                else:
                    # try to move around a bubble that you collide with
                    # find colliding bubble
                    for colliding in self.collides_with(new_bubble, rest_bub
                        # calculate direction vector
                        dir_vec = rest_bub[colliding, :2] - self.bubbles[i,
                        dir_vec = dir_vec / np.sqrt(dir_vec.dot(dir_vec))
                        # calculate orthogonal vector
                        orth = np.array([dir_vec[1], -dir_vec[0]])
                        # test which direction to go
                        new_point1 = (self.bubbles[i, :2] + orth *
                                      self.step_dist)
                        new_point2 = (self.bubbles[i, :2] - orth *
                                      self.step_dist)
                        dist1 = self.center_distance(
                            self.com, np.array([new_point1]))
                        dist2 = self.center_distance(
                            self.com, np.array([new_point2]))
                        new_point = new_point1 if dist1 < dist2 else new_poi
                        new_bubble = np.append(new_point, self.bubbles[i, 2:
                        if not self.check_collisions(new_bubble, rest_bub):
                            self.bubbles[i, :] = new_bubble
                            self.com = self.center_of_mass()
```

```
            if moves / len(self.bubbles) < 0.1:
                self.step_dist = self.step_dist / 2

    def plot(self, ax, labels, colors):
        for i in range(len(self.bubbles)):
            if i < len(labels) and i < len(colors):
                # Scale the radius to increase the bubble size
                radius = 1 * self.bubbles[i, 2]
                circ = plt.Circle(
                    self.bubbles[i, :2], radius, color=colors[i])
                ax.add_patch(circ)


                percentage = (self.bubbles[i, 3] / np.sum(self.bubbles[:, 3]
                ax.text(*self.bubbles[i, :2], f"{percentage:.1f}%",
                        horizontalalignment='center', verticalalignment='cer

        legend_labels = [f'{label}' for label in labels]
        ax.legend(legend_labels, loc='center left', bbox_to_anchor=(1, 0.5))

income_means = [first, second, third, fourth, fifth, sixth, seventh, eight,
labels = ['<$10,000', '$10,000-$14,999', '$15,000-$24,999', '$25,000-$34,999
colors = ['#5A69AF', '#579E65', '#F9C784', '#FC944A', '#F24C00', '#00B825',

bubble_chart = BubbleChart(income_means, bubble_spacing=0.1)
bubble_chart.collapse()
custom_colors = ['#5A69AF', '#579E65', '#F9C784', '#FC944A', '#F24C00', '#00


fig, ax = plt.subplots(subplot_kw=dict(aspect="equal"))
bubble_chart.plot(ax, labels, colors= custom_colors)
ax.axis("off")
ax.relim()
ax.autoscale_view()
ax.set_title('Income Distribution')

plt.show()
```



ADD INSIGHTS HERE####

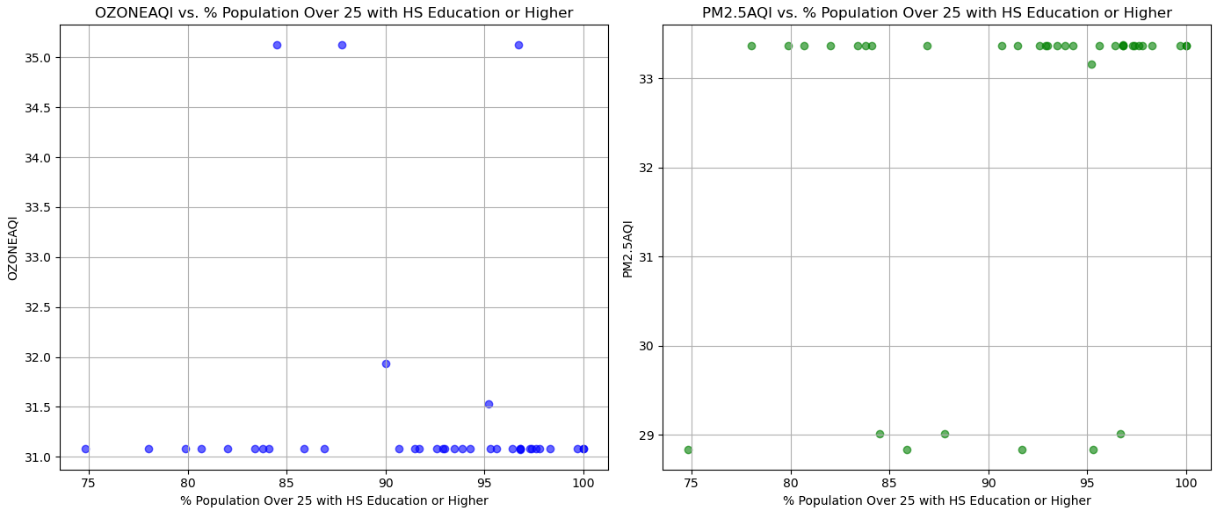
CENSUS DATA

In [30]:
```
census = pd.read_csv('census.csv')
air_data_clean = pd.read_csv('2021_data.csv')
```

In [31]:
```
#Merging DP03 and AQI on zipcodes.
census2 = air_data_clean.merge(census, left_on='zip_code', right_on='Zipcode
```

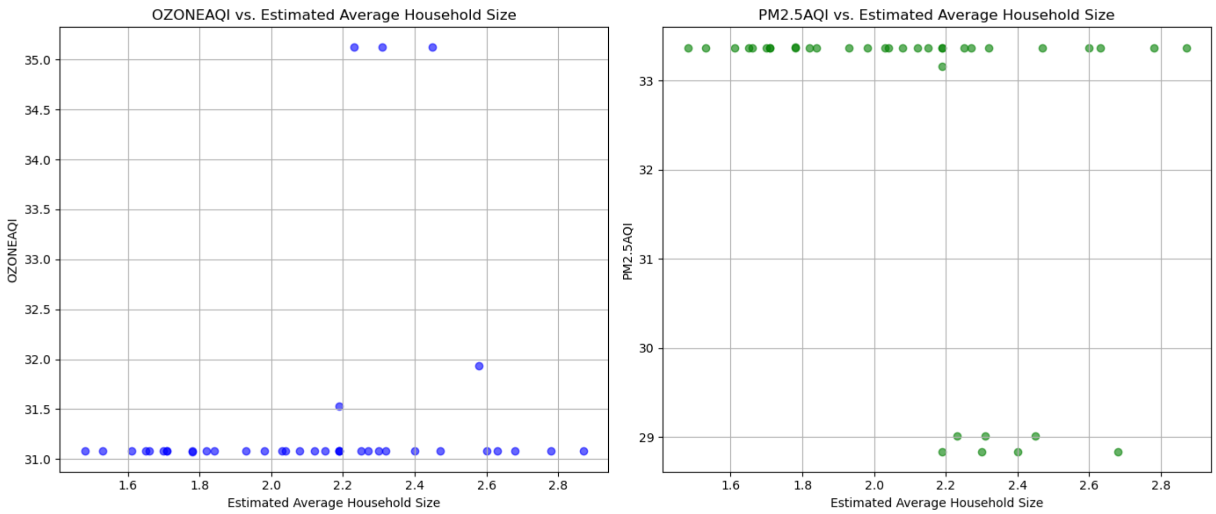
In [32]:
```
plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.scatter(census2['Percent_Population_Over_25_Education_Attainment_High sc
            census2['OZONEAQI'], color='blue', alpha=0.6)
plt.title('OZONEAQI vs. % Population Over 25 with HS Education or Higher')
plt.xlabel('% Population Over 25 with HS Education or Higher')
plt.ylabel('OZONEAQI')
plt.grid(True)

# Scatter plot for PM2.5AQI vs Percent_Population_Over_25_Education_Attainme
plt.subplot(1, 2, 2)
plt.scatter(census2['Percent_Population_Over_25_Education_Attainment_High sc
            census2['PM2.5AQI'], color='green', alpha=0.6)
plt.title('PM2.5AQI vs. % Population Over 25 with HS Education or Higher')
plt.xlabel('% Population Over 25 with HS Education or Higher')
plt.ylabel('PM2.5AQI')
plt.grid(True)
```

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



ADD INSIGHT HERE

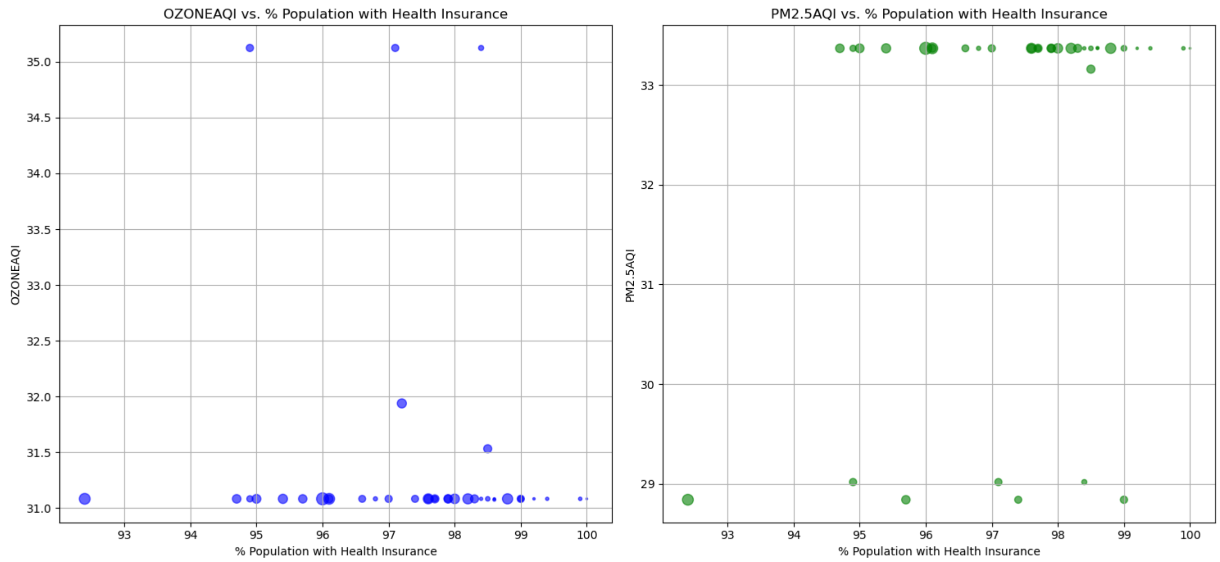
In [33]:
```
plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.scatter(census2['Estimated_Average_Household_Size'], census2['OZONEAQI']
plt.title('OZONEAQI vs. Estimated Average Household Size')
plt.xlabel('Estimated Average Household Size')
plt.ylabel('OZONEAQI')
plt.grid(True)

# Scatter plot for PM2.5AQI vs Estimated_Average_Household_Size
plt.subplot(1, 2, 2)
plt.scatter(census2['Estimated_Average_Household_Size'], census2['PM2.5AQI']
plt.title('PM2.5AQI vs. Estimated Average Household Size')
plt.xlabel('Estimated Average Household Size')
plt.ylabel('PM2.5AQI')
plt.grid(True)

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



ADD INSIGHT HERE

In [34]:
```
census_transport_2 = air_data_clean.merge(census_transport, left_on='zip_coc
```

In [35]:
```
plt.figure(figsize=(15, 7))

plt.subplot(1, 2, 1)
plt.scatter(census_transport_2['Percent_Civilian_Noninstitutionalized_Popula
            census_transport_2['OZONEAQI'],
            s=census_transport_2['Estimated_Civilian_Noninstitutionalized_Po
            color='blue', alpha=0.6)
plt.title('OZONEAQI vs. % Population with Health Insurance')
plt.xlabel('% Population with Health Insurance')
plt.ylabel('OZONEAQI')
plt.grid(True)

# Bubble plot for PM2.5AQI vs Percent with health insurance coverage
plt.subplot(1, 2, 2)
plt.scatter(census_transport_2['Percent_Civilian_Noninstitutionalized_Popula
            census_transport_2['PM2.5AQI'],
            s=census_transport_2['Estimated_Civilian_Noninstitutionalized_Po
            color='green', alpha=0.6)
plt.title('PM2.5AQI vs. % Population with Health Insurance')
plt.xlabel('% Population with Health Insurance')
plt.ylabel('PM2.5AQI')
plt.grid(True)

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



ADD INSIGHT HERE

In [ ]: