Analysis_4_1

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Homework 4-1

In this assignment, you'll again work with the Medicare Advantage data. These data are described in detail in the Medicare Advantage GitHub Repo. We worked with a subset of these data back in assignment 1; however, this assignment requires that you work with a more complete version of the Medicare Advantage data. We'll again focus on the years 2010-2015. Once you have the data downloaded and the code running, answer the following questions:

The due date for initial submission is 4/7, the revision due date is 4/9, and the final due date is Friday, 4/11.

[96]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from IPython.display import display
import statsmodels.api as sm

# Load the final cleaned data
final_data = pd.read_csv("/Users/kathrynmawhinney/Documents/GitHub/Homework4/
  ↪data/output/final_ma_data.csv")
```

```
/var/folders/8p/wmnjrdd55rx2pn76f5j7m2tw0000gn/T/ipykernel_20352/2552217010.py:9
: DtypeWarning: Columns (68,98,99,100,101,102,103,104,105,106) have mixed types.
Specify dtype option on import or set low_memory=False.
  final_data = pd.read_csv("/Users/kathrynmawhinney/Documents/GitHub/Homework4/d
ata/output/final_ma_data.csv")
```

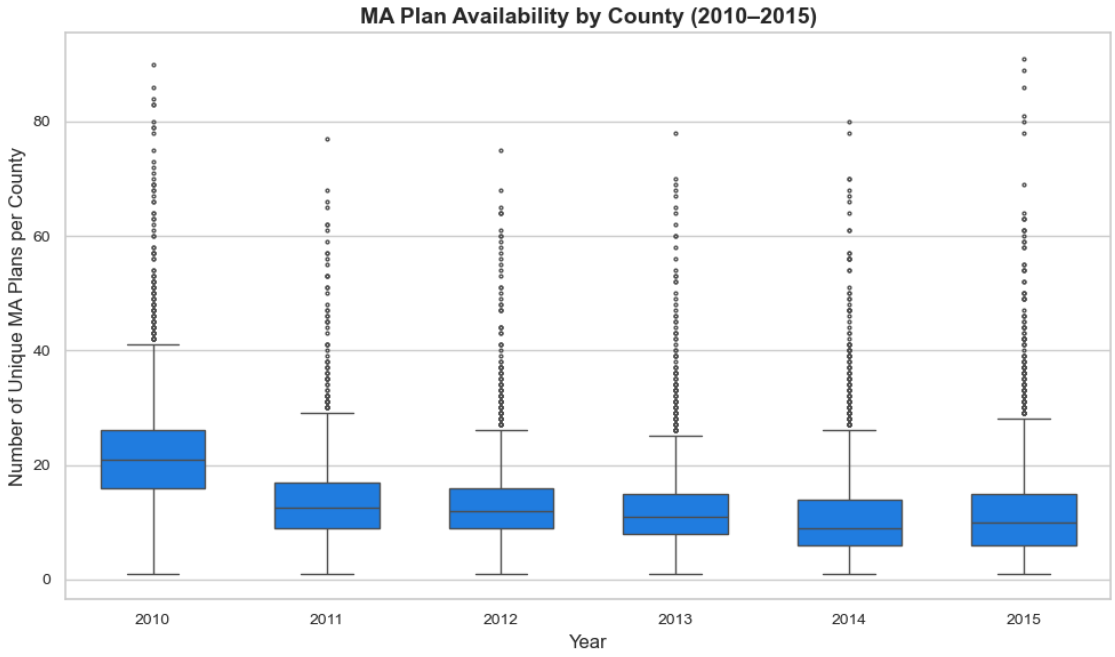
0.0.1 Summarize the Data

1. Remove all SNPs, 800-series plans, and prescription drug only plans (i.e., plans that do not offer Part C benefits). Provide a box and whisker plot showing the distribution of plan counts by county over time. Do you think that the number of plans is sufficient, too few, or too many?

[97]:
```
# Confirm that all SNPs are removed
print("Any SNPs remaining?", final_data["snp"].unique())

# Confirm that no planid is in the 800-899 range (inclusive)
print("Any 800-series plans?", final_data[(final_data["planid"] >= 800) &␣
 ↪(final_data["planid"] < 900)].shape[0])

# Confirm that all remaining plans offer Part C benefits (i.e., are not PDPs)
# If there's a `plan_type` or `partd` column, check for drug-only plans
if "plan_type" in final_data.columns:
    print("Plan types present:", final_data["plan_type"].unique())

if "partd" in final_data.columns:
    print("Any Part D only plans?", final_data["partd"].unique())
```

```
Any SNPs remaining? ['No']
Any 800-series plans? 0
Plan types present: ['Local PPO' 'National PACE' 'HMO/HMOPOS'
 'Continuing Care Retirement Community' '1876 Cost' 'PFFS' 'ESRD I'
 'PSO (State License)' 'MSA' 'Regional PPO'
 'Medicare-Medicaid Plan HMO/HMOPOS']
Any Part D only plans? ['Yes' 'No']
```

[98]:
```
# Set seaborn style
sns.set(style="whitegrid")

# Plot
plt.figure(figsize=(10, 6))
sns.boxplot(
    data=plan_counts,
    x="year",
    y="num_plans",
    color="#007BFF",  # Bright blue
    width=0.6,
    fliersize=2  # smaller outlier dots
)

# Titles and labels
plt.title("MA Plan Availability by County (2010-2015)", fontsize=14,␣
 ↪weight='bold')
plt.xlabel("Year", fontsize=12)
plt.ylabel("Number of Unique MA Plans per County", fontsize=12)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.tight_layout()
plt.show()
```

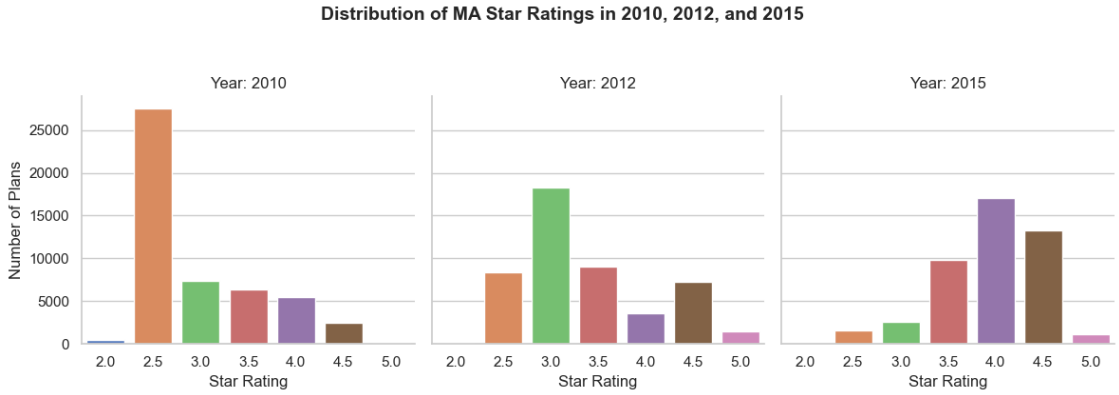


2. Provide bar graphs showing the distribution of star ratings in 2010, 2012, and 2015. How has this distribution changed over time?

[99]:
```
# Filter the data for only 2010, 2012, and 2015
selected_years = [2010, 2012, 2015]
rating_subset = final_data[final_data["year"].isin(selected_years)]

# Drop rows where Star_Rating is missing
rating_subset = rating_subset.dropna(subset=["Star_Rating"])

# Set plot style
sns.set(style="whitegrid")

# Create bar plots by year
g = sns.catplot(
    data=rating_subset,
    x="Star_Rating",
    col="year",
    kind="count",
    col_order=selected_years,
    height=4,
    aspect=1,
    palette="muted"
)

# Labeling
```

```
g.set_axis_labels("Star Rating", "Number of Plans")
g.set_titles("Year: {col_name}")
g.fig.suptitle("Distribution of MA Star Ratings in 2010, 2012, and 2015", y=1.
 ↪05, fontsize=14, weight='bold')

# Display
plt.tight_layout()
plt.show()
```

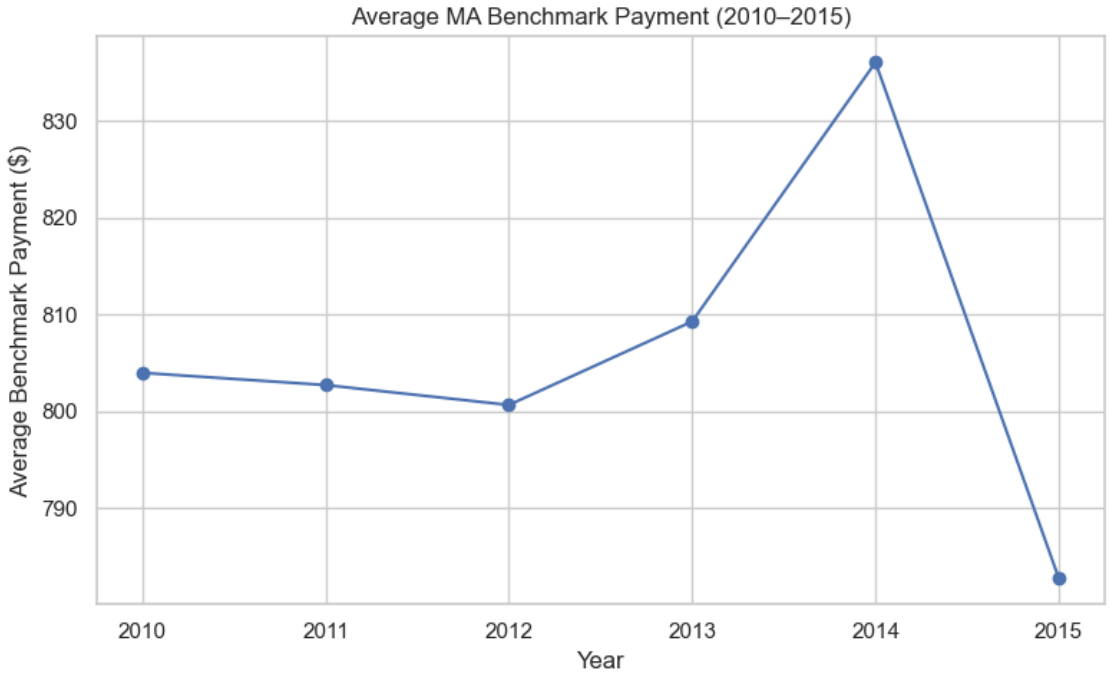
```
/var/folders/8p/wmnjrdd55rx2pn76f5j7m2tw0000gn/T/ipykernel_20352/1622397608.py:1
2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  g = sns.catplot(
```



3. Plot the average benchmark payment over time from 2010 through 2015. How much has the average benchmark payment risen over the years?

[100]:
```
# Calculate the average benchmark payment by year
benchmark_avg = (
    final_data
    .groupby("year", as_index=False)
    .agg(avg_benchmark=("ma_rate", "mean"))
)

# Plot
plt.figure(figsize=(8, 5))
plt.plot(benchmark_avg["year"], benchmark_avg["avg_benchmark"], marker='o')
plt.title("Average MA Benchmark Payment (2010-2015)")
plt.xlabel("Year")
```

```
plt.ylabel("Average Benchmark Payment ($)")
plt.grid(True)
plt.tight_layout()
plt.show()

# Display average changes
print(benchmark_avg)
print(f"\nIncrease from 2010 to 2015: ${benchmark_avg['avg_benchmark'].iloc[-1]␣
  ↪- benchmark_avg['avg_benchmark'].iloc[0]:.2f}")
```

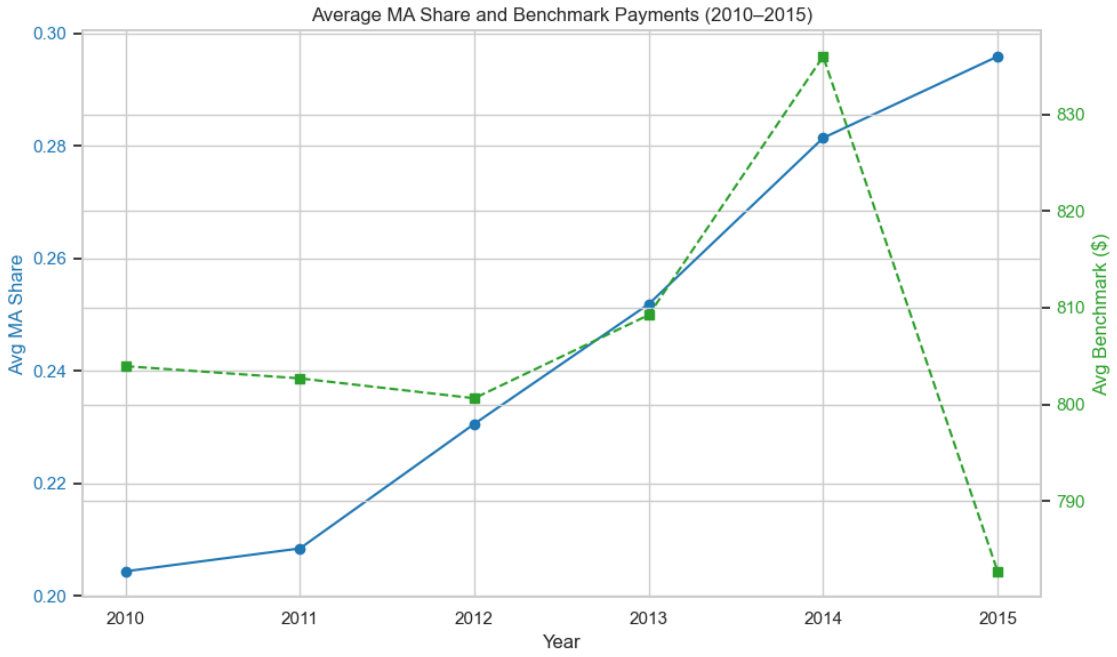



```
   year  avg_benchmark
0  2010     803.948611
1  2011     802.684419
2  2012     800.626973
3  2013     809.254803
4  2014     836.013611
5  2015     782.711741

Increase from 2010 to 2015: $-21.24
```

4. Plot the average share of Medicare Advantage (relative to all Medicare eligibles) over time from 2010 through 2015. Has Medicare Advantage increased or decreased in popularity? How does this share correlate with benchmark payments?

[101]:
```
# Step 1: Create MA share in the penetration data
ma_penetration_data["ma_share"] = (
    ma_penetration_data["avg_enrolled"] / ma_penetration_data["avg_eligibles"]
)

# Step 2: Merge the MA share into final_data
final_data = final_data.merge(
    ma_penetration_data[["fips", "year", "ma_share"]],
    on=["fips", "year"],
    how="left"
)
```

[102]:
```
# Group and compute averages
penetration_trend = (
    final_data
    .groupby("year", as_index=False)
    .agg(
        avg_ma_share=("ma_share", "mean"),
        avg_benchmark=("ma_rate", "mean")
    )
)

fig, ax1 = plt.subplots(figsize=(10, 6))
color = 'tab:blue'
ax1.set_xlabel("Year")
ax1.set_ylabel("Avg MA Share", color=color)
ax1.plot(penetration_trend["year"], penetration_trend["avg_ma_share"],␣
 ↪marker="o", color=color)
ax1.tick_params(axis='y', labelcolor=color)
ax2 = ax1.twinx()  # second y-axis
color = 'tab:green'
ax2.set_ylabel("Avg Benchmark ($)", color=color)
ax2.plot(penetration_trend["year"], penetration_trend["avg_benchmark"],␣
 ↪marker="s", linestyle="--", color=color)
ax2.tick_params(axis='y', labelcolor=color)
plt.title("Average MA Share and Benchmark Payments (2010-2015)")
fig.tight_layout()
plt.show()
```



0.0.2 Estimate ATEs

For the rest of the assignment, we'll use a regression discontinuity design to estimate the average treatment effect from receiving a marginally higher rating. We'll focus only on 2010.

5. Calculate the running variable underlying the star rating. Provide a table showing the number of plans that are rounded up into a 3-star, 3.5-star, 4-star, 4.5-star, and 5-star rating.

[103]:
```
data_2010 = final_data[final_data["year"] == 2010].copy()

data_2010["Star_Rating"] = np.where(
    data_2010["partd"] == "No",
    data_2010["partc_score"],
    np.where(
        data_2010["partcd_score"].isna(),
        data_2010["partc_score"],
        data_2010["partcd_score"]
    )
)

data_2010["raw_rating"] = data_2010["Star_Rating"]

data_2010["rounded_rating"] = np.round(data_2010["raw_rating"] * 2) / 2

rating_counts_df = rating_counts.reset_index()
rating_counts_df.columns = ["Rounded Star Rating", "Number of Plans"]
```

```
display(rating_counts_df)
```

	Rounded Star Rating	Number of Plans
0	3.0	7419
1	3.5	6347
2	4.0	5453
3	4.5	2459
4	5.0	75

6. Using the RD estimator with a bandwidth of 0.125, provide an estimate of the effect of receiving a 3-star versus a 2.5 star rating on enrollments. Repeat the exercise to estimate the effects at 3.5 stars, and summarize your results in a table.

[104]:
```
def rd_estimate(data, cutoff, bandwidth=0.125):
    # Subset to within the bandwidth
    rd_data = data[
        (data["raw_rating"] >= cutoff - bandwidth) &
        (data["raw_rating"] <= cutoff + bandwidth)
    ].copy()

    # Treatment indicator: 1 if raw rating is above cutoff (gets rounded up),␣
 ↪else 0
    rd_data["treatment"] = (rd_data["raw_rating"] >= cutoff).astype(int)

    # Drop missing enrollment values
    rd_data = rd_data.dropna(subset=["avg_enrolled"])

    # Add constant for regression
    X = sm.add_constant(rd_data["treatment"])
    y = rd_data["avg_enrolled"]

    model = sm.OLS(y, X).fit()

    # Return the coefficient and standard error of treatment effect
    return model.params["treatment"], model.bse["treatment"]

# Estimate ATEs at 3.0 and 3.5 cutoffs
ate_3_0, se_3_0 = rd_estimate(data_2010, cutoff=3.0)
ate_3_5, se_3_5 = rd_estimate(data_2010, cutoff=3.5)

# Create summary table
summary_df = pd.DataFrame({
    "Cutoff": [3.0, 3.5],
    "Estimated ATE on Enrollment": [ate_3_0, ate_3_5],
    "Standard Error": [se_3_0, se_3_5]
})

display(summary_df)
```

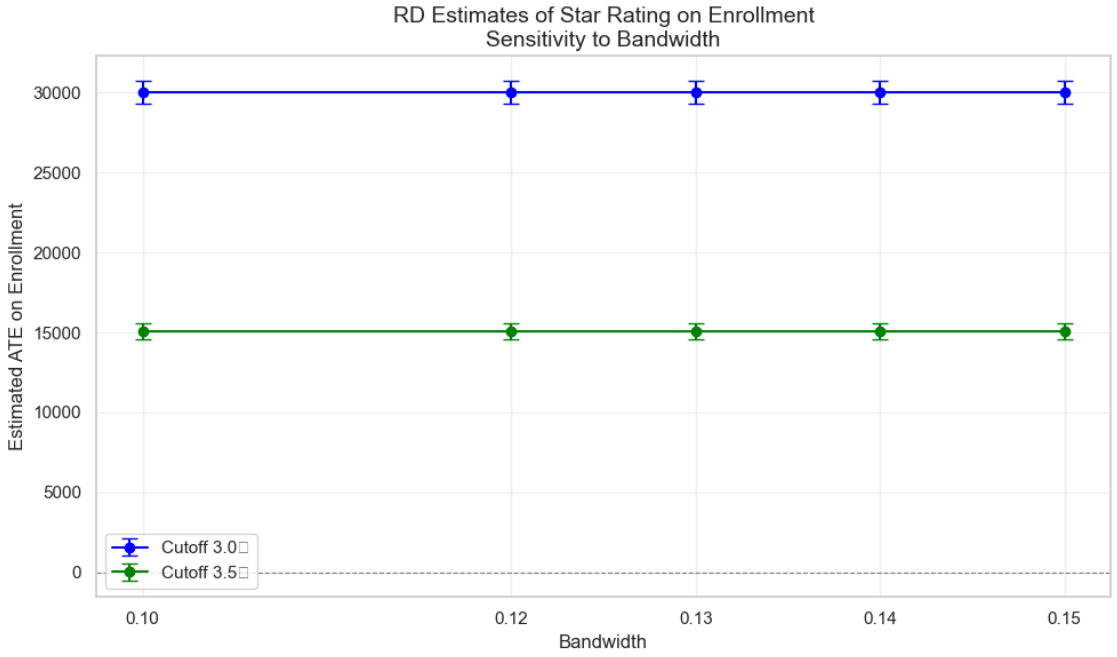
```
   Cutoff  Estimated ATE on Enrollment  Standard Error
0     3.0                  30053.87533      715.591694
1     3.5                  15051.38263      503.656124
```

7. Repeat your results for bandwidhts of 0.1, 0.12, 0.13, 0.14, and 0.15 (again for 3 and 3.5 stars). Show all of the results in a graph. How sensitive are your findings to the choice of bandwidth?

[105]:
```
bandwidths = [0.1, 0.12, 0.13, 0.14, 0.15]
results = []

for bw in bandwidths:
    for cutoff in [3.0, 3.5]:
        ate, se = rd_estimate(data_2010, cutoff=cutoff, bandwidth=bw)
        results.append({
            "Cutoff": cutoff,
            "Bandwidth": bw,
            "ATE": ate,
            "SE": se
        })

# Convert to DataFrame
rd_results = pd.DataFrame(results)

# Plot setup
fig, ax = plt.subplots(figsize=(10, 6))
for cutoff, color in zip([3.0, 3.5], ['blue', 'green']):
    subset = rd_results[rd_results["Cutoff"] == cutoff]
    ax.errorbar(subset["Bandwidth"], subset["ATE"], yerr=subset["SE"],
                label=f'Cutoff {cutoff} ', marker='o', linestyle='-',
                color=color, capsize=5)

# Styling
ax.set_title("RD Estimates of Star Rating on Enrollment\nSensitivity to␣
 ↪Bandwidth", fontsize=14)
ax.set_xlabel("Bandwidth")
ax.set_ylabel("Estimated ATE on Enrollment")
ax.axhline(0, color='gray', linestyle='--', linewidth=0.8)
ax.legend()
plt.xticks(bandwidths)
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()
```

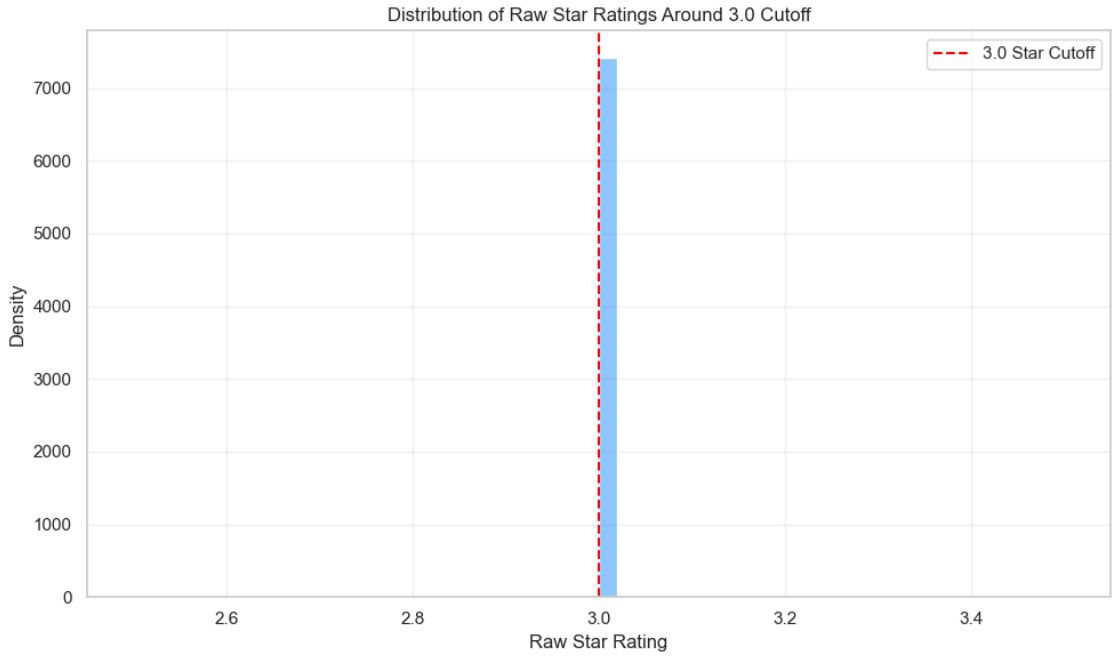
```
/var/folders/8p/wmnjrdd55rx2pn76f5j7m2tw0000gn/T/ipykernel_20352/920963729.py:33
: UserWarning: Glyph 9733 (\N{BLACK STAR}) missing from font(s) Arial.
  plt.tight_layout()
/opt/anaconda3/lib/python3.12/site-packages/IPython/core/pylabtools.py:170:
```

```
UserWarning: Glyph 9733 (\N{BLACK STAR}) missing from font(s) Arial.
  fig.canvas.print_figure(bytes_io, **kw)
```

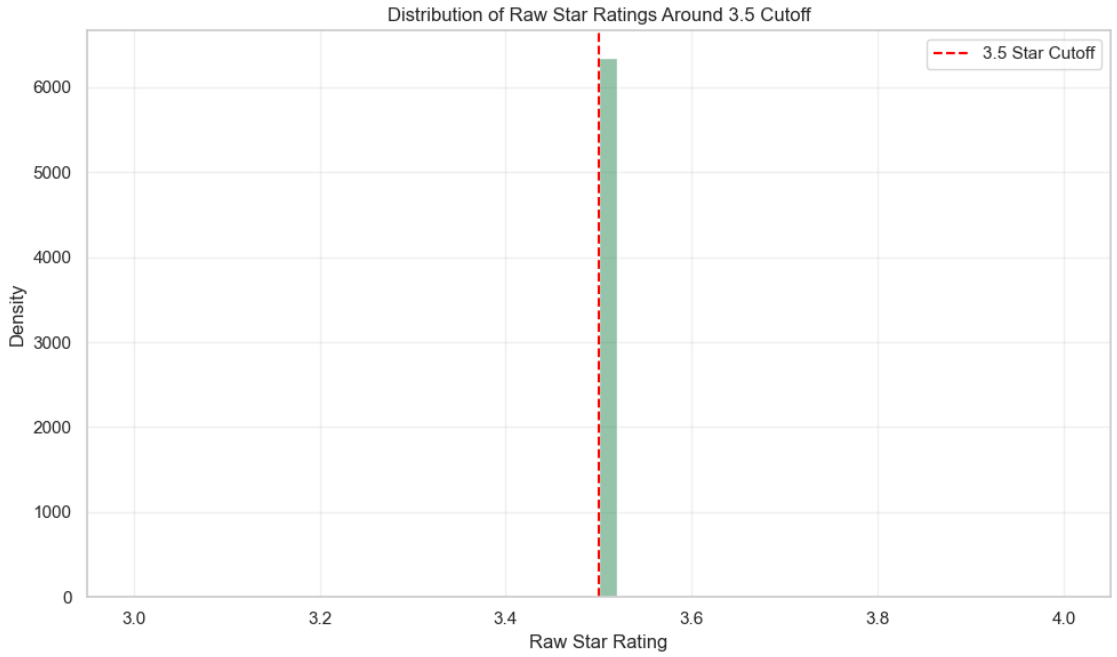


8. Examine (graphically) whether contracts appear to manipulate the running variable. In other words, look at the distribution of the running variable before and after the relevent threshold values. What do you find?

[106]:
```
# Filter data around the 3.0 cutoff
cutoff = 3.0
bandwidth = 0.3
subset = data_2010[(data_2010["raw_rating"] >= cutoff - bandwidth) &␣
 ↪(data_2010["raw_rating"] <= cutoff + bandwidth)]

# Plot
plt.figure(figsize=(10, 6))
sns.histplot(subset["raw_rating"], bins=50, kde=True, color='dodgerblue',␣
 ↪edgecolor='white')
plt.axvline(x=cutoff, color='red', linestyle='--', label='3.0 Star Cutoff')

plt.title("Distribution of Raw Star Ratings Around 3.0 Cutoff")
plt.xlabel("Raw Star Rating")
plt.ylabel("Density")
plt.legend()
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()
```



[107]:
```
# Filter data around the 3.5 cutoff
cutoff = 3.5
subset = data_2010[(data_2010["raw_rating"] >= cutoff - bandwidth) &␣
 ↪(data_2010["raw_rating"] <= cutoff + bandwidth)]

# Plot
plt.figure(figsize=(10, 6))
sns.histplot(subset["raw_rating"], bins=50, kde=True, color='seagreen',␣
 ↪edgecolor='white')
plt.axvline(x=cutoff, color='red', linestyle='--', label='3.5 Star Cutoff')

plt.title("Distribution of Raw Star Ratings Around 3.5 Cutoff")
plt.xlabel("Raw Star Rating")
plt.ylabel("Density")
plt.legend()
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()
```



9. Similar to question 4, examine whether plans just above the threshold values have different characteristics than contracts just below the threshold values. Use HMO and Part D status as your plan characteristics.

[109]:
```
# Focus on 2010 and create raw_rating if not already there
data_2010 = final_data[final_data["year"] == 2010].copy()
data_2010["raw_rating"] = data_2010["Star_Rating"]

# Function to summarize covariates above/below RD cutoff
def covariate_check(data, cutoff, bandwidth):
    subset = data[(data["raw_rating"] >= cutoff - bandwidth) &␣
 ↪(data["raw_rating"] <= cutoff + bandwidth)].copy()
    subset["above"] = (subset["raw_rating"] >= cutoff).astype(int)

    summary = subset.groupby("above").agg(
        share_hmo=("plan_type", lambda x: (x == "HMO").mean()),
        share_partd=("partd", lambda x: (x == "Yes").mean()),
        n_plans=("contractid", "count")
    ).reset_index()

    summary["group"] = summary["above"].map({0: f"Below {cutoff}", 1: f"Above␣
 ↪{cutoff}"})
    return summary[["group", "share_hmo", "share_partd", "n_plans"]]

# Run for both thresholds
cov_3 = covariate_check(data_2010, cutoff=3.0, bandwidth=0.125)
```

```
cov_35 = covariate_check(data_2010, cutoff=3.5, bandwidth=0.125)

# Combine results
covariate_table = pd.concat([cov_3, cov_35], ignore_index=True)
covariate_table.columns = ["Group", "Share HMO", "Share Part D", "Number of␣
 ↪Plans"]

# Display the final table
print("\nCovariate Balance Around RD Thresholds (Bandwidth = 0.125)")
display(covariate_table)
```

```
Covariate Balance Around RD Thresholds (Bandwidth = 0.125)
```

	Group	Share HMO	Share Part D	Number of Plans
0	Above 3.0	0.0	0.893651	7419
1	Above 3.5	0.0	0.853317	6347

10. Summarize your findings from 5-9. What is the effect of increasing a star rating on enrollments? Briefly explain your results.