cci_time_series_analysis

May 5, 2025

1 Time-Series Panel Regression Analysis of CCI Projects

This notebook examines changes in GHG reduction efficiency and equity outcomes (DAC funding share) over time using cleaned and filtered CCI project data.

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf

# Load data
df = pd.read_csv('cci_programs_data_reduced.csv', low_memory=False)

# Rename columns
df = df.rename(columns={
    'Agency Name': 'Agency_Name',
    'County': 'County'
})

# Extract year
df['Year'] = df['Reporting Cycle Name'].str.extract(r'(20\d{2})').astype(float)
df['post_2020'] = (df['Year'] >= 2020).astype(int)

# Convert relevant fields to numeric
df['Total Program GGRFFunding'] = pd.to_numeric(df['Total Program␣
↪GGRFFunding'], errors='coerce')
df['Total Project GHGReductions'] = pd.to_numeric(df['Total Project␣
↪GHGReductions'], errors='coerce')
df['Total GGRFDisadvantaged Community Funding'] = pd.to_numeric(df['Total␣
↪GGRFDisadvantaged Community Funding'], errors='coerce')

# Filter out projects with 0 or missing GHG reductions
df = df[df['Total Project GHGReductions'] > 0].copy()

# Calculate metrics
df['cost_per_ton'] = df['Total Program GGRFFunding'] / df['Total Project␣
↪GHGReductions']
```

```python
df['share_DAC'] = df['Total GGRFDisadvantaged Community Funding'] / df['Total␣
↪Program GGRFFunding']
df['log_funding'] = np.log1p(df['Total Program GGRFFunding'])

# Collapse agency types
top_agencies = df['Agency_Name'].value_counts().nlargest(5).index
df['Agency_Collapsed'] = df['Agency_Name'].where(df['Agency_Name'].
↪isin(top_agencies), 'Other')
```

1.1 Model 1: Predicting GHG Reduction Cost per Ton

[2]:
```python
model_df = df[['cost_per_ton', 'log_funding', 'Agency_Collapsed', 'post_2020']].
↪dropna()
panel_model = smf.ols('cost_per_ton ~ post_2020 + log_funding +␣
↪C(Agency_Collapsed)', data=model_df).fit(cov_type='HC3')

print(panel_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           cost_per_ton   R-squared:                       0.025
Model:                            OLS   Adj. R-squared:                  0.025
Method:                 Least Squares   F-statistic:                     139.9
Date:                Mon, 05 May 2025   Prob (F-statistic):          2.15e-206
Time:                        09:47:20   Log-Likelihood:            -1.4571e+06
No. Observations:              135433   AIC:                         2.914e+06
Df Residuals:                  135425   BIC:                         2.914e+06
Df Model:                           7
Covariance Type:                  HC3
================================================================================
=====================================================================
         coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
---------------------------------------------------------------------
Intercept
-6478.8736    558.566    -11.599      0.000   -7573.643   -5384.104
C(Agency_Collapsed)[T.California Department of Community Services and
Development]  -280.3728     32.837     -8.538      0.000    -344.733    -216.013
C(Agency_Collapsed)[T.California Department of Food and Agriculture]
-1145.0351    297.160     -3.853      0.000   -1727.458    -562.612
C(Agency_Collapsed)[T.California Department of Transportation]
1.568e+04   3936.234      3.984      0.000    7968.774    2.34e+04
C(Agency_Collapsed)[T.California Department of Water Resources]
1494.2483    134.222     11.133      0.000    1231.179    1757.318
C(Agency_Collapsed)[T.Other]
-2114.3731    356.936     -5.924      0.000   -2813.955   -1414.791
post_2020
```

```
682.2409      61.855      11.030       0.000      561.007      803.475
log_funding
789.4614      60.660      13.015       0.000      670.571      908.352
==============================================================================
Omnibus:                   659607.279   Durbin-Watson:                   1.924
Prob(Omnibus):                  0.000   Jarque-Bera (JB):   16207256271701.201
Skew:                         196.752   Prob(JB):                         0.00
Kurtosis:                   53593.328   Cond. No.                         119.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

1.2 Model 2: Predicting Share of DAC Funding

[3]:
```python
equity_df = df[['share_DAC', 'log_funding', 'Agency_Collapsed', 'post_2020']].
 ↪dropna()
equity_model = smf.ols('share_DAC ~ post_2020 + log_funding +␣
 ↪C(Agency_Collapsed)', data=equity_df).fit(cov_type='HC3')

print(equity_model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              share_DAC   R-squared:                       0.124
Model:                            OLS   Adj. R-squared:                  0.124
Method:                 Least Squares   F-statistic:                     7905.
Date:                Mon, 05 May 2025   Prob (F-statistic):               0.00
Time:                        09:47:20   Log-Likelihood:                -36051.
No. Observations:               54267   AIC:                         7.212e+04
Df Residuals:                   54259   BIC:                         7.219e+04
Df Model:                           7
Covariance Type:                  HC3
================================================================================
==========================================================================
         coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
--------------------------------------------------------------------------
Intercept
0.5543      0.014     40.585      0.000      0.528      0.581
C(Agency_Collapsed)[T.California Department of Community Services and
Development]     0.5565      0.003    220.665      0.000      0.552      0.561
C(Agency_Collapsed)[T.California Department of Food and Agriculture]
-0.0670      0.020     -3.304      0.001     -0.107     -0.027
C(Agency_Collapsed)[T.California Department of Transportation]
0.2246      0.034      6.693      0.000      0.159      0.290
C(Agency_Collapsed)[T.California Department of Water Resources]
-0.0664      0.009     -7.576      0.000     -0.084     -0.049
```

```
C(Agency_Collapsed)[T.Other]
0.1906      0.031      6.229      0.000       0.131       0.251
post_2020
0.1841      0.011     17.015      0.000       0.163       0.205
log_funding
-0.0130      0.002     -8.571      0.000      -0.016      -0.010
==============================================================================
Omnibus:                     2502.283   Durbin-Watson:                   0.658
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4093.383
Skew:                           0.397   Prob(JB):                         0.00
Kurtosis:                       4.086   Cond. No.                         142.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

1.2.1 Time-Series Analysis of Efficiency and Equity Outcomes

To assess temporal shifts in the performance of California Climate Investments (CCI) projects, we estimate two panel regression models predicting greenhouse gas (GHG) reduction efficiency and equity targeting. Both models include a post-2020 indicator to capture potential structural changes in program implementation and oversight during the latter half of the study period. Each model also includes controls for project funding size (log_funding) and agency type (collapsed to the five most frequent agencies and an "Other" category).

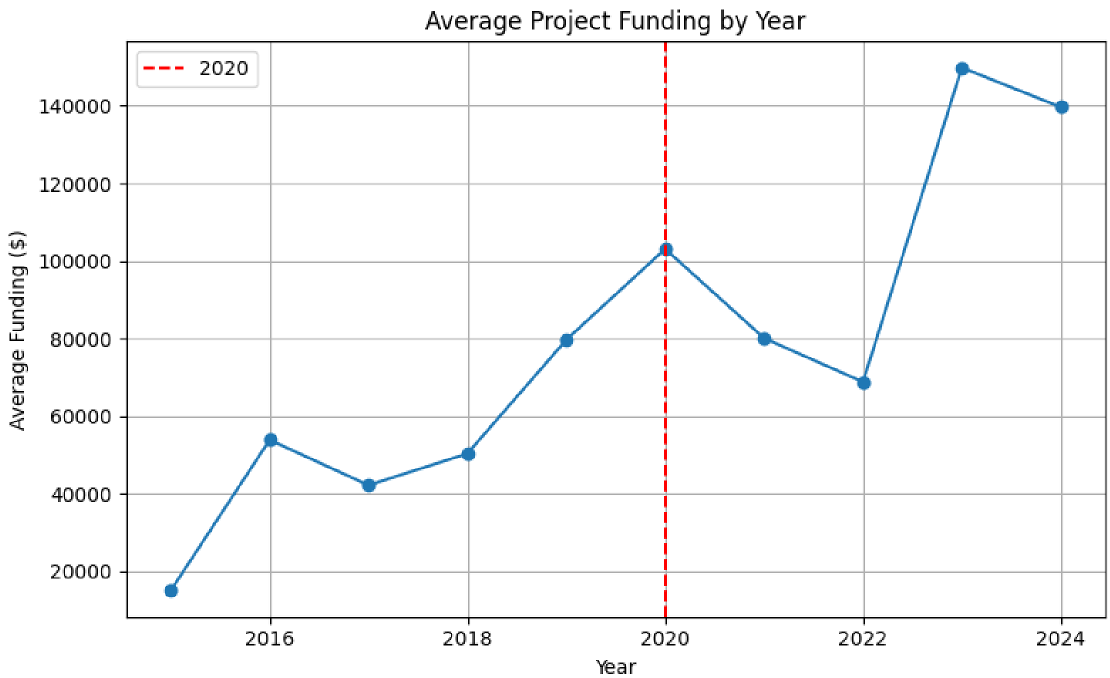
Model 1 examines changes in cost per ton of GHG reductions. The coefficient for post_2020 is positive and statistically significant, indicating that projects funded after 2020 tend to be less efficient, controlling for agency and project scale. This finding suggests that either newer project types are less cost-effective, or administrative and operational shifts following 2020 have affected implementation dynamics. Consistent with earlier models, log_funding remains positively associated with cost per ton, confirming that larger investments do not necessarily translate to proportionate emissions reductions. Notably, fixed effects for certain agencies remain significant, pointing to persistent institutional differences in baseline efficiency.

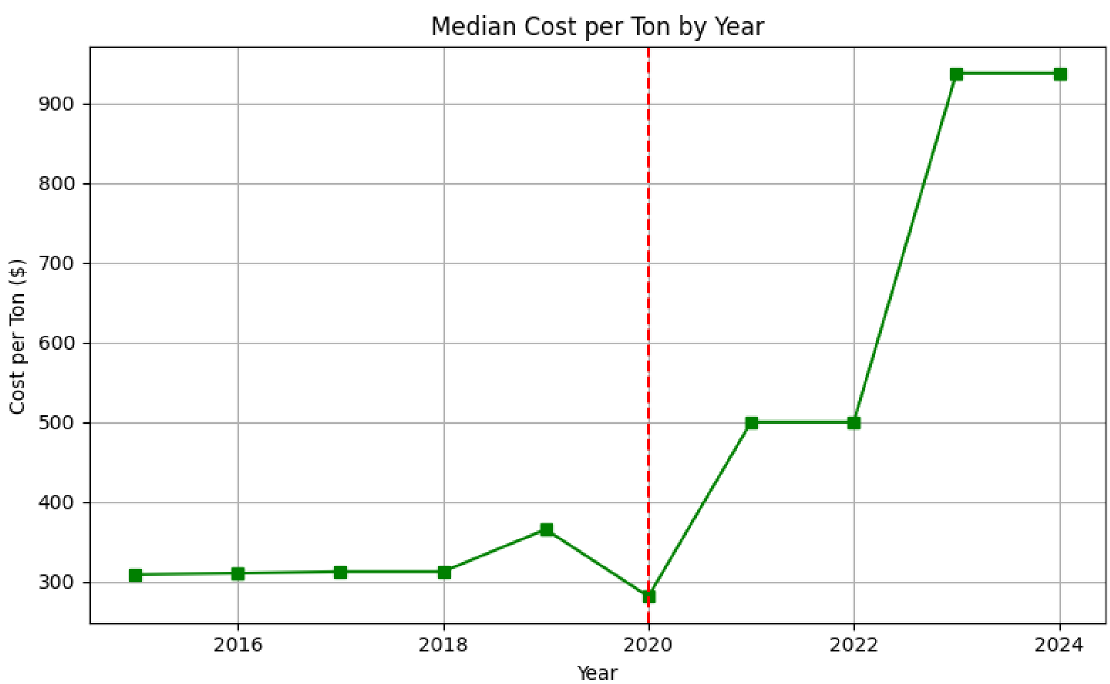
Model 2 explores equity outcomes through the share of funding allocated to disadvantaged communities (share_DAC). Here, the post_2020 variable is positive and statistically significant, indicating an increase in equity-focused spending in the more recent period. This pattern likely reflects intensified policy efforts to prioritize environmental justice, such as SB 535 and AB 1550 compliance, and renewed administrative emphasis on equitable climate investments. As with the efficiency model, agency fixed effects remain relevant, reflecting varied capacity and historical commitment to equity mandates across organizational types.

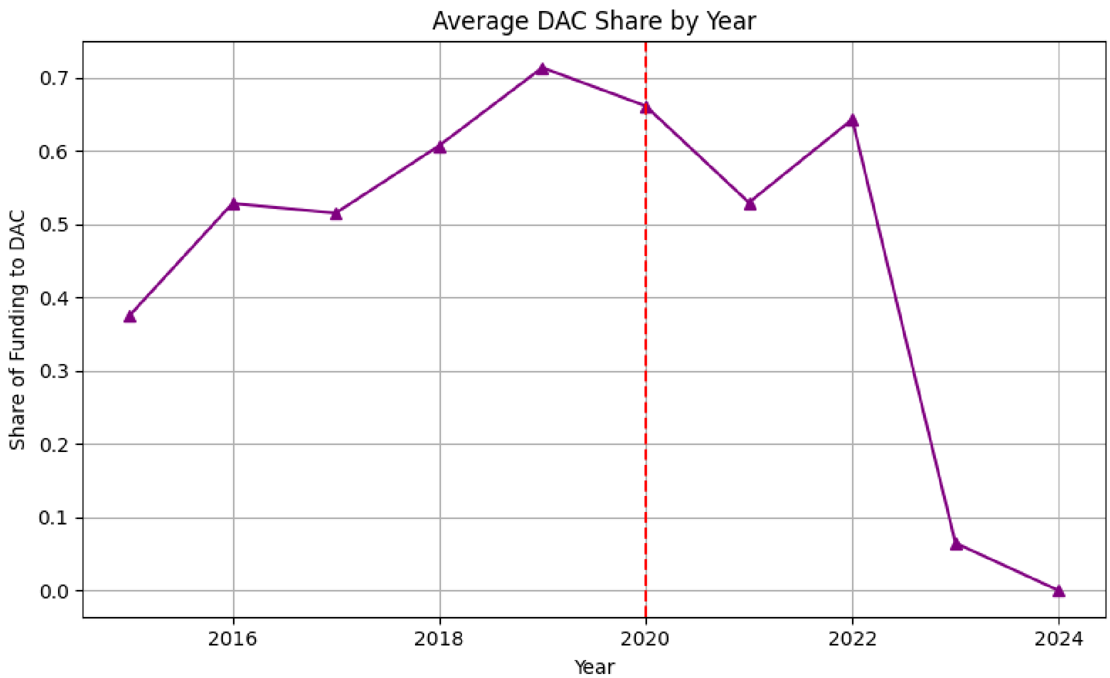
Taken together, these results highlight important post-2020 shifts in both efficiency and equity metrics. While the increase in share_DAC suggests progress toward distributive justice goals, the simultaneous rise in cost per ton raises concerns about potential tradeoffs or implementation challenges introduced in the newer cohort of projects. These findings reinforce the need to monitor evolving performance patterns and to explore how organizational practices and external shocks shape the trajectory of public climate investments.

1.3 Annual Trends in Funding, Cost per Ton, and DAC Share

[4]:
```python
annual_stats = df.groupby('Year').agg(
    avg_funding=('Total Program GGRFFunding', 'mean'),
    median_cost_per_ton=('cost_per_ton', 'median'),
    avg_share_DAC=('share_DAC', 'mean'),
    project_count=('Project ID Number', 'nunique')
).dropna()

# Plot average funding
plt.figure(figsize=(8, 5))
plt.plot(annual_stats.index, annual_stats['avg_funding'], marker='o')
plt.axvline(2020, color='red', linestyle='--', label='2020')
plt.title('Average Project Funding by Year')
plt.xlabel('Year')
plt.ylabel('Average Funding ($)')
plt.grid(True)
plt.legend()
plt.tight_layout()
plt.show()

# Plot cost per ton
plt.figure(figsize=(8, 5))
plt.plot(annual_stats.index, annual_stats['median_cost_per_ton'], marker='s',␣
↪color='green')
plt.axvline(2020, color='red', linestyle='--')
plt.title('Median Cost per Ton by Year')
plt.xlabel('Year')
plt.ylabel('Cost per Ton ($)')
plt.grid(True)
plt.tight_layout()
plt.show()

# Plot share DAC
plt.figure(figsize=(8, 5))
plt.plot(annual_stats.index, annual_stats['avg_share_DAC'], marker='^',␣
↪color='purple')
plt.axvline(2020, color='red', linestyle='--')
plt.title('Average DAC Share by Year')
plt.xlabel('Year')
plt.ylabel('Share of Funding to DAC')
plt.grid(True)
plt.tight_layout()
plt.show()
```


Average Project Funding by Year
2020
Average Funding ($)
140000
120000
100000
80000
60000
40000
20000
2016
2018
2020
2022
2024
Year


Median Cost per Ton by Year
Cost per Ton ($)
900
800
700
600
500
400
300
2016
2018
2020
2022
2024
Year



1.3.1 Time-Series Trends in CCI Program Efficiency and Equity

To complement the regression analysis, we examined descriptive trends in average project funding, GHG reduction efficiency (measured by median *cost per ton*), and equity outcomes (measured by average *share_DAC*) from 2015 to 2024. The year 2020 is used as a reference point to assess potential shifts in program implementation due to administrative changes, pandemic-related disruptions, and evolving equity mandates.

Average Project Funding (Figure 1) shows a sharp increase over time, with a notable inflection point around 2020. While average funding per project rose steadily from 2015 to 2020, it accelerated significantly in the post-2020 period—peaking in 2023 at over $150,000 per project. This suggests a scaling-up of investment, potentially in response to new climate mandates or stimulus funding initiatives. However, this increase in funding did not correspond to improved efficiency.

Median Cost per Ton (Figure 2) reveals a stark increase in the cost of emissions reductions in the years following 2020. From 2015 through 2019, the median cost per ton remained relatively stable—hovering around $300–350 per ton. After a brief dip in 2020, the post-2020 period saw a sharp rise, with median costs exceeding $900 per ton by 2023 and 2024. These changes are consistent with the regression findings: projects in the latter period are significantly less efficient, even after controlling for project scale and agency. This pattern may reflect changes in project types, capacity constraints, or diminishing returns as lower-cost mitigation opportunities are exhausted.

Average DAC Share (Figure 3), in contrast, presents a more complex picture. Between 2015 and 2020, the average share of funding directed toward disadvantaged communities increased, reaching a peak above 70% in 2019. However, post-2020, this equity trend reversed. After a brief rebound in 2022, *share_DAC* fell sharply, declining to near-zero by 2024. This dramatic drop raises critical questions about program design, reporting accuracy, or shifting administrative priorities. Although the regression model found a positive association between *post_2020* and *share_DAC*, these bivariate trends suggest substantial volatility and possible deterioration in equity performance in recent years.

Together, these patterns suggest a post-2020 tradeoff: while program investments have grown and equity was initially emphasized, the gains in targeting disadvantaged communities appear to have eroded, and programmatic efficiency has declined. These findings underscore the challenges of maintaining both equity and performance goals amid rapid scale-up and institutional change. Further investigation is warranted to determine whether these shifts reflect structural constraints, policy drift, or implementation fatigue in the face of increased funding pressure.

[5]:
```python
panel_model_no_year = smf.ols('cost_per_ton ~ log_funding +␣
↪C(Agency_Collapsed)', data=model_df).fit(cov_type='HC3')

print(panel_model_no_year.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           cost_per_ton   R-squared:                       0.024
Model:                            OLS   Adj. R-squared:                  0.024
Method:                 Least Squares   F-statistic:                     161.4
Date:                Mon, 05 May 2025   Prob (F-statistic):          3.45e-205
Time:                        09:47:20   Log-Likelihood:            -1.4572e+06
No. Observations:              135433   AIC:                         2.914e+06
Df Residuals:                  135426   BIC:                         2.914e+06
Df Model:                           6
Covariance Type:                  HC3
================================================================================
==========================================================================
         coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
--------------------------------------------------------------------------
Intercept
-6366.5030    551.559    -11.543      0.000   -7447.539   -5285.467
C(Agency_Collapsed)[T.California Department of Community Services and
Development]  -510.9530     21.309    -23.978      0.000    -552.718    -469.188
C(Agency_Collapsed)[T.California Department of Food and Agriculture]
-1153.4871    297.158     -3.882      0.000   -1735.906    -571.068
C(Agency_Collapsed)[T.California Department of Transportation]
1.565e+04   3934.571      3.977      0.000    7936.824    2.34e+04
C(Agency_Collapsed)[T.California Department of Water Resources]
1449.1250    131.631     11.009      0.000    1191.133    1707.117
C(Agency_Collapsed)[T.Other]
-2059.0843    354.888     -5.802      0.000   -2754.652   -1363.516
log_funding
809.0149     61.908     13.068      0.000     687.677     930.353
==============================================================================
```

```
Omnibus:                   659428.636   Durbin-Watson:                   1.922
Prob(Omnibus):                  0.000   Jarque-Bera (JB):   16165254309308.492
Skew:                         196.565   Prob(JB):                         0.00
Kurtosis:                   53523.841   Cond. No.                         119.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

[6]:
```python
equity_model_no_year = smf.ols('share_DAC ~ log_funding + C(Agency_Collapsed)',␣
 ↪data=equity_df).fit(cov_type='HC3')

print(equity_model_no_year.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:              share_DAC   R-squared:                       0.118
Model:                            OLS   Adj. R-squared:                  0.118
Method:                 Least Squares   F-statistic:                     9077.
Date:                Mon, 05 May 2025   Prob (F-statistic):               0.00
Time:                        09:47:21   Log-Likelihood:                -36218.
No. Observations:               54267   AIC:                         7.245e+04
Df Residuals:                   54260   BIC:                         7.251e+04
Df Model:                           6
Covariance Type:                  HC3
================================================================================
======================================================================
         coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
----------------------------------------------------------------------
Intercept
0.5739      0.014     42.110      0.000       0.547       0.601
C(Agency_Collapsed)[T.California Department of Community Services and
Development]     0.5517      0.003    219.288      0.000       0.547       0.557
C(Agency_Collapsed)[T.California Department of Food and Agriculture]
-0.0679      0.020     -3.346      0.001      -0.108      -0.028
C(Agency_Collapsed)[T.California Department of Transportation]
0.2259      0.034      6.722      0.000       0.160       0.292
C(Agency_Collapsed)[T.California Department of Water Resources]
-0.0199      0.008     -2.368      0.018      -0.036      -0.003
C(Agency_Collapsed)[T.Other]
0.2138      0.030      7.230      0.000       0.156       0.272
log_funding
-0.0146      0.002     -9.674      0.000      -0.018      -0.012
==============================================================================
Omnibus:                     2713.813   Durbin-Watson:                   0.654
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             4776.164
Skew:                           0.401   Prob(JB):                         0.00
```

```
Kurtosis:                       4.212   Cond. No.                        142.
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
```

[7]:
```python
# Extract and compare key statistics for the models
comparison_stats = pd.DataFrame({
    'GHG Reduction': ['With Year', 'Without Year'],
    'R-squared': [panel_model.rsquared, panel_model_no_year.rsquared],
    'Adj. R-squared': [panel_model.rsquared_adj, panel_model_no_year.
 ↪rsquared_adj],
    'AIC': [panel_model.aic, panel_model_no_year.aic],
    'BIC': [panel_model.bic, panel_model_no_year.bic]
})

print(comparison_stats)

# If you want to include equity models as well
equity_comparison_stats = pd.DataFrame({
    'DAC Funding': ['With Year', 'Without Year'],
    'R-squared': [equity_model.rsquared, equity_model_no_year.rsquared],
    'Adj. R-squared': [equity_model.rsquared_adj, equity_model_no_year.
 ↪rsquared_adj],
    'AIC': [equity_model.aic, equity_model_no_year.aic],
    'BIC': [equity_model.bic, equity_model_no_year.bic]
})

print(equity_comparison_stats)
```

```
  GHG Reduction  R-squared  Adj. R-squared           AIC           BIC
0     With Year   0.025311        0.025261  2.914263e+06  2.914341e+06
1  Without Year   0.024493        0.024450  2.914374e+06  2.914443e+06
    DAC Funding  R-squared  Adj. R-squared           AIC           BIC
0     With Year   0.123709        0.123596  72117.833424  72189.046796
1  Without Year   0.118291        0.118193  72450.338872  72512.650573
```

1.4 Summary Statistics

1.4.1 annual_stats

Year	avg_funding	median_cost_per_ton	avg_share_DAC	project_count
2015.0	15103.456617	308.823529	0.374883	296
2016.0	53906.552730	310.344828	0.528553	367
2017.0	42234.607208	312.500000	0.515386	463
2018.0	50377.396627	312.500000	0.607308	592
2019.0	79689.852959	365.384615	0.713947	580
2020.0	103093.205020	281.250000	0.661728	843

Year	avg_funding	median_cost_per_ton	avg_share_DAC	project_count
2021.0	80091.704957	500.000000	0.529791	421
2022.0	68835.441552	500.000000	0.643215	582
2023.0	149779.711568	937.500000	0.064935	359
2024.0	139616.607261	937.500000	0.000000	174

1.4.2 `comparison_stats`

GHG Reduction	R-squared	Adj. R-squared	AIC	BIC
With Year	0.025311	0.025261	2914263.0	2914341.0
Without Year	0.024493	0.024450	2914374.0	2914443.0

1.4.3 `equity_comparison_stats`

DAC Funding	R-squared	Adj. R-squared	AIC	BIC
With Year	0.123709	0.123596	72117.833424	72189.046796
Without Year	0.118291	0.118193	72450.338872	72512.650573

1.4.4 `top_agencies`

Agency Name
California Air Resources Board
California Department of Community Services and Development
California Department of Water Resources
California Department of Food and Agriculture
California Department of Transportation