cci_spatial_analysis

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1 Spatial Analysis & Propensity Score Matching (CCI Projects)

This notebook performs a spatial and collaborative analysis of CCI projects using propensity score matching to assess the impact of high-collaboration efforts on GHG efficiency and equity.

```
[1]: # Imports
  import pandas as pd
  import numpy as np
  import statsmodels.api as sm
  import matplotlib.pyplot as plt
  import seaborn as sns
```

```
[9]: # Aggregate project-level data
project_df = df.groupby('Project ID Number').agg({
        'log_funding': 'first',
        'Agency_Name': 'first',
        'County': 'first',
        'cost_per_ton': 'first',
        'share_DAC': 'first'
}).reset_index()
```

```
# Add region and collaboration features
      project_df['n_partners'] = df.groupby('Project ID Number')['County'].nunique().
       ⇔values
      project_df['high_collab'] = (project_df['n_partners'] > 5).astype(int)
      south_counties = ["Los Angeles", "Orange", "San Diego", "Riverside", "San_
       →Bernardino", "Imperial", "Ventura"]
      project_df['Region_South'] = project_df['County'].isin(south_counties).
       →astype(int)
      # Drop rows with missing data in modeling variables
      project_df = project_df.dropna(subset=['log_funding', 'Agency_Name', __
       ⇔'Region_South', 'high_collab'])
[10]: # Build covariate matrix for PSM
      covariates = ['log_funding', 'Agency_Name', 'Region_South']
      X = pd.get_dummies(project_df[covariates], drop_first=True).astype(float)
      y = project_df['high_collab'].astype(int)
      # Fit logistic regression (PSM)
      ps_model = sm.Logit(y, sm.add_constant(X)).fit(method='lbfgs', maxiter=500,__
       ⇔disp=0)
     project_df['propensity'] = ps_model.predict(sm.add_constant(X))
     /Users/dpadams/Repos/new_california_equity/.venv/lib/python3.13/site-
     packages/statsmodels/base/model.py:595: HessianInversionWarning: Inverting
     hessian failed, no bse or cov_params available
       warnings.warn('Inverting hessian failed, no bse or cov_params '
 [5]: # Perform nearest neighbor matching
      treated = project_df[project_df['high_collab'] == 1]
      control = project_df[project_df['high_collab'] == 0]
      matches = []
      for idx, p in treated['propensity'].items():
          closest_idx = (control['propensity'] - p).abs().idxmin()
          matches.append((idx, closest_idx))
      matched_idx = [i for pair in matches for i in pair]
      matched_sample = project_df.loc[matched_idx]
 [6]: # Clean out extreme or invalid values
      matched_sample = matched_sample.replace([np.inf, -np.inf], np.nan).

dropna(subset=['cost_per_ton', 'share_DAC'])
     matched_treated = matched_sample[matched_sample['high_collab'] == 1]
```

```
matched_control = matched_sample[matched_sample['high_collab'] == 0]

# Summary statistics
print("High-collab avg $/ton:", matched_treated['cost_per_ton'].mean())
print("Low-collab avg $/ton:", matched_control['cost_per_ton'].mean())
print("High-collab avg share_DAC:", matched_treated['share_DAC'].mean())
print("Low-collab avg share_DAC:", matched_control['share_DAC'].mean())
```

High-collab avg \$/ton: 544.4898966105618 Low-collab avg \$/ton: 7262.068465753554 High-collab avg share_DAC: 0.7419354838709677 Low-collab avg share_DAC: 0.42857142857142855

```
[7]: # Plot comparisons
fig, axs = plt.subplots(1, 2, figsize=(12, 5))

sns.boxplot(x='high_collab', y='cost_per_ton', data=matched_sample, ax=axs[0])
axs[0].set_title('GHG Cost per Ton by Collaboration Level')
axs[0].set_xlabel('High Collaboration (0=Low, 1=High)')
axs[0].set_ylabel('Cost per Ton ($)')

sns.boxplot(x='high_collab', y='share_DAC', data=matched_sample, ax=axs[1])
axs[1].set_title('DAC Funding Share by Collaboration Level')
axs[1].set_xlabel('High Collaboration (0=Low, 1=High)')
axs[1].set_ylabel('Share of Funding to DAC')

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

