01_exploratory_analysis

November 29, 2025

1 Exploratory Analysis of Synthetic Panel Data

This notebook provides a brief exploratory analysis of the synthetic panel dataset generated in this repository.

The goals are to:

- Inspect the structure and summary statistics of the data
- Visualize outcomes over time for treated vs. control units
- Build intuition for the difference in differences (DiD) setup

The dataset was generated by `generate_data.py` and saved to `data/processed/sim_panel.csv`. Each row corresponds to a unit–time observation with:

- `unit_id`: unit identifier (e.g., firm or region)
- `time`: time period (integer)
- `treated`: 1 if the unit is ever treated, 0 otherwise
- `post`: 1 if the period is after the policy starts, 0 otherwise
- `treat_post`: interaction of `treated * post` (the DiD term)
- `x1`, `x2`: additional covariates
- `y`: outcome variable

1.1 Imports & Settings

[1]:
```
import os

import pandas as pd
import matplotlib.pyplot as plt
import numpy as np

# Make plots a bit bigger by default
plt.rcParams["figure.figsize"] = (8, 5)
```

```python
# Show pandas floats with fewer decimals for readability
pd.options.display.float_format = "{:.3f}".format
```

1.2 Load Data

[2]:
```python
# Construct path to the processed data
notebook_dir = os.path.dirname(os.getcwd())  # parent of notebooks/
data_path = os.path.join(notebook_dir, "data", "processed", "sim_panel.csv")

print("Loading data from:", data_path)
df = pd.read_csv(data_path)

df.head()
```

```
Loading data from: d:\GitHub\coding-sample\data\processed\sim_panel.csv
```

[2]:

	unit_id	time	treated	post	treat_post	x1	x2	y
0	1	1	0	0	0	1.191	0.263	3.922
1	1	2	0	0	0	-1.745	0.927	2.529
2	1	3	0	0	0	-1.110	-0.472	3.376
3	1	4	0	0	0	0.052	-0.292	3.836
4	1	5	0	0	0	-0.252	0.153	5.425

1.3 Quick Data Description

1.4 Basic Structure and Summary

We start by checking:

- The number of units and time periods
- The balance of treated vs. control units
- Basic summary statistics for the main variables

1.5 Shape, Unique Counts, Summary Stats

[3]:
```python
n_rows, n_cols = df.shape
n_units = df["unit_id"].nunique()
n_periods = df["time"].nunique()

print(f"Rows: {n_rows}, Columns: {n_cols}")
print(f"Unique units: {n_units}")
print(f"Unique time periods: {n_periods}")

print("\nTreated vs. control units (count):")
print(df.groupby("treated")["unit_id"].nunique())
```

```
print("\nSummary statistics:")
df[["y", "treated", "post", "treat_post", "x1", "x2"]].describe()
```

```
Rows: 2000, Columns: 8
Unique units: 200
Unique time periods: 10

Treated vs. control units (count):
treated
0    120
1     80
Name: unit_id, dtype: int64

Summary statistics:
```

[3]:

	y	treated	post	treat_post	x1	x2
count	2000.000	2000.000	2000.000	2000.000	2000.000	2000.000
mean	3.811	0.400	0.500	0.200	-0.023	0.020
std	1.886	0.490	0.500	0.400	1.023	0.983
min	-2.407	0.000	0.000	0.000	-4.389	-3.110
25%	2.492	0.000	0.000	0.000	-0.714	-0.635
50%	3.772	0.000	0.500	0.000	0.010	0.008
75%	5.158	1.000	1.000	0.000	0.645	0.703
max	10.257	1.000	1.000	1.000	3.241	3.208

1.6 Average Outcome Over Time by Treatment Status

To build intuition for the DiD setting, we plot average outcomes over time separately for:

- Units that are **ever treated** (`treated = 1`)
- Units that are **never treated** (`treated = 0`)

In a typical DiD setup, we are interested in whether the treated units experience a differential change in outcomes after the policy starts, relative to the control units.

1.7 Compute Group Means and Plot

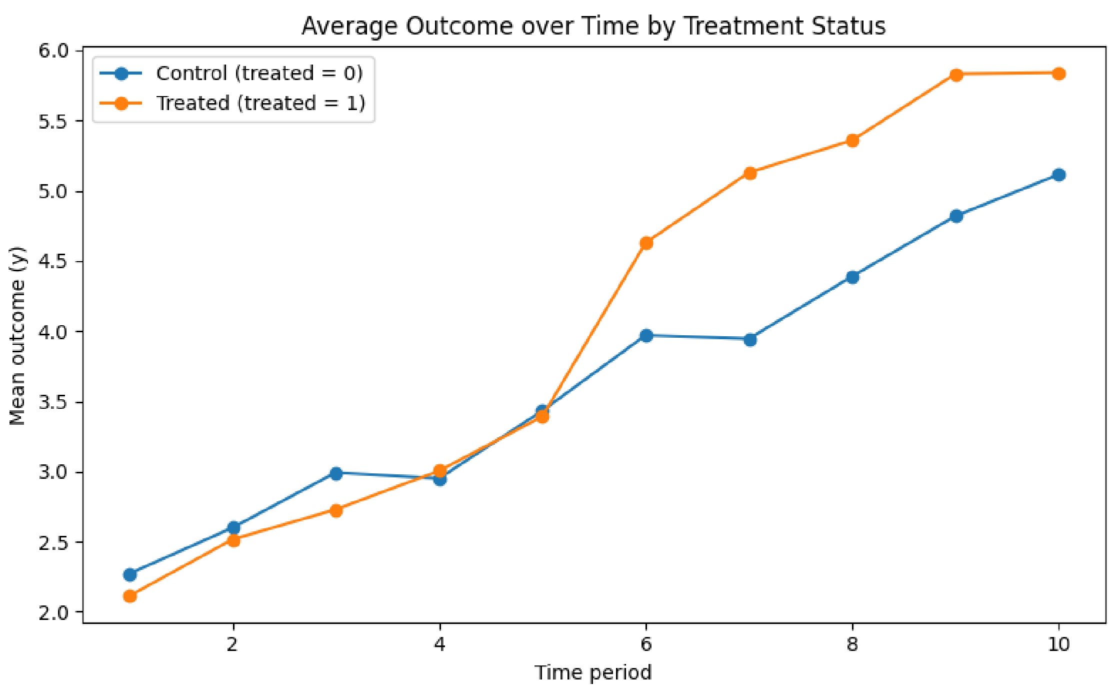
[4]:
```
# Compute mean outcome by time and treatment status
mean_y = (
    df.groupby(["time", "treated"])["y"]
    .mean()
    .reset_index()
    .pivot(index="time", columns="treated", values="y")
)

mean_y.columns = ["control_mean_y", "treated_mean_y"]
mean_y
```

[4]:

time	control_mean_y	treated_mean_y
1	2.271	2.112
2	2.599	2.516
3	2.992	2.729
4	2.950	3.004
5	3.432	3.391
6	3.970	4.629
7	3.945	5.129
8	4.390	5.359
9	4.820	5.832
10	5.115	5.841

[5]:

```
# Line plot of average outcome over time for treated vs control
ax = mean_y.plot(marker="o")
ax.set_title("Average Outcome over Time by Treatment Status")
ax.set_xlabel("Time period")
ax.set_ylabel("Mean outcome (y)")
ax.legend(["Control (treated = 0)", "Treated (treated = 1)"])
plt.tight_layout()
plt.show()
```



1.8 Pre vs Post Policy Comparison

Next, we look at how average outcomes change **before** and **after** the policy:

- For treated units
- For control units

This connects directly to the DiD intuition.

[6]:
```python
# Average outcome by treated x post
pre_post_summary = (
    df.groupby(["treated", "post"])["y"]
    .mean()
    .reset_index()
    .pivot(index="treated", columns="post", values="y")
)

pre_post_summary.columns = ["pre_policy_mean_y", "post_policy_mean_y"]
pre_post_summary.index = ["control (0)", "treated (1)"]

pre_post_summary
```

[6]:

	pre_policy_mean_y	post_policy_mean_y
control (0)	2.849	4.448
treated (1)	2.750	5.358

[7]:
```python
# Compute simple differences
pre_post_summary["change"] = (
    pre_post_summary["post_policy_mean_y"] -
 ↪pre_post_summary["pre_policy_mean_y"]
)
pre_post_summary
```

[7]:

	pre_policy_mean_y	post_policy_mean_y	change
control (0)	2.849	4.448	1.599
treated (1)	2.750	5.358	2.608

1.9 Connecting to Difference in Differences

From the table above:

- The change for control units captures background trends over time
- The change for treated units reflects both background trends and the policy effect

The difference-in-differences estimate is computed as:

(change in average outcome for treated units) minus (change in average outcome for control units).

Below we compute this quantity directly from the summary table.

[8]:
```python
delta_control = pre_post_summary.loc["control (0)", "change"]
delta_treated = pre_post_summary.loc["treated (1)", "change"]
```

```
did_estimate = float(delta_treated - delta_control)

print(f"Change (control): {delta_control:.3f}")
print(f"Change (treated): {delta_treated:.3f}")
print(f"Difference in differences estimate: {did_estimate:.3f}")
```

```
Change (control): 1.599
Change (treated): 2.608
Difference in differences estimate: 1.008
```

1.10 Optional: Compare to Regression-Based DiD Estimate

The script `analysis_diff_in_diff.py` fits a regression model of the form:

Outcome = unit fixed effects
+ time fixed effects
+ (treated $\times$ post)
+ controls (x1, x2)
+ error

The coefficient on `treated:post` is the regression-based DiD estimate.
In the synthetic data generation process, the true policy effect was set to be around 1.0.

You can:

- Run the script from the command line to see the full regression table, or
- Replicate the regression here in the notebook if you would like to explore specification choices.