Project Structure: Clearing the Air?

- **Summarize the Paper's Research Questions and Answers**
  - **Question:** The paper examines the effectiveness of U.S. gasoline content regulations—specifically restrictions intended to reduce Volatile Organic Compound (VOC) emissions—in reducing **ground-level ozone pollution**.
  - **Answer:** The authors find that **flexible federal gasoline standards** (like RVP limits) which allow refiners to choose the compliance mechanism, **did not significantly improve air quality**. They attribute this to refiners removing the least-cost, but least ozone-reactive, VOCs. However, they find that the more **precisely targeted, inflexible California regulations (CARB RFG)**, which mandated the removal of particularly harmful compounds, **significantly improved air quality** in the Los Angeles-San Diego area.
- **Describe the Datasets Used in Answering the Question**
  - The study uses **daily measurements of ambient ozone concentrations** from hundreds of air quality monitors across the United States.
  - The data covers the period from **1989–2003**.
  - The analysis exploits the **rich spatial and temporal variation** in the implementation of the various gasoline regulations (e.g., RVP 9.5, RVP 7.8, Federal RFG, CARB RFG) across different counties and time periods.
- **Clean the Data Set**
  - Download the original, uncleaned air quality data and policy data (found on openICPSR or the AEA website).
  - The data must be merged and filtered to create the analysis sample. For example, you will likely need to:
    - Aggregate daily monitor data to a relevant time/space level (e.g., county-month or monitor-season).
    - Limit the time window to the main analysis period (e.g., 1989–2003).
    - Handle missing or irregular observations (e.g., monitors with incomplete data).
    - Create the key treatment variables (binary indicators for the presence of different regulations like Federal RFG or CARB RFG).
  - *Self-Correction Note:* It is acceptable if your cleaning process does not exactly match the authors'.
- **Replicate and Interpret a Summary Statistics Table**
  - Replicate a summary table presenting distributional characteristics (mean, median, IQR) for key variables:
    - **Outcome:** Ozone concentration (e.g., 8-hour max ozone, in ppb).
    - **Treatment Indicators:** Dummy variables for the federal and California regulations (e.g., mean represents the proportion of observations under that regulation).
    - **Key Covariates:** Time-varying local characteristics, such as daily maximum temperature, which is a key control in air quality studies.

Replicate the Main Results

- **Describe the Empirical Method and State Assumptions**
    - **Method:** The researchers primarily use a **Difference-in-Differences (DiD) design** and a **Regression Discontinuity (RD) design** to identify the impacts of the regulations.
        - The DiD approach exploits the **spatial and temporal variation** in the introduction of regulations across different areas and time periods.
    - **Assumptions (DiD):** The primary identification assumption is the **Parallel Trends Assumption**.
        - **English:** In the absence of the gasoline regulation (the treatment), the air quality in the areas that adopted the regulation (treatment group) would have followed the same trend over time as the air quality in the areas that did not (control group).
        - Mathematics: Using a standard DiD panel setup with fixed effects, the identifying assumption is that the time-varying unobserved confounders are the same for the treatment and control groups:
          $$E[\mu_{it} \mid T_i=1, t \ge t^*] - E[\mu_{it} \mid T_i=1, t < t^*] = E[\mu_{it} \mid T_i=0, t \ge t^*] - E[\mu_{it} \mid T_i=0, t < t^*]$$
          where μ_{it} is the unobserved error term, T_i is the treatment group indicator, and t^* is the policy adoption time.
- **Replicate the Main Result and Interpret it in English**
    - Replicate the primary DiD regression. The main result will be the estimated coefficient on the interaction term ($\text{Treated} \times \text{Post}$), which represents the causal effect of the regulation.
    - **Interpretation:** For example, you might interpret the coefficient as: "The introduction of the Federal Reformulated Gasoline (RFG) regulation had an estimated effect of $[X]$ ppb on ground-level ozone, which is not statistically significant.".
- **Critically Appraise the Stated Assumptions for Causal Identification**
    - **Confounding Factors:** Critique the **Parallel Trends Assumption**. Consider if the *timing* of the federal regulation coincided with other events that could independently affect air quality in the treated areas but not the control areas. Examples could include:
        - Other environmental regulations (e.g., industrial emissions controls).
        - Significant local economic changes or population shifts.
    - **Endogenous Response:** The authors highlight a key confounding factor: refiners' **behavioral response**. The *flexibility* of the federal regulation allowed refiners to remove the least costly (but least effective) VOCs, potentially undermining the intended policy effect. This means the **"treatment" was not what the regulators intended**, which is a powerful critique of the policy's design, if not the DiD method itself.

Replicate Robustness Checks/Extensions

- **Pick and Replicate a Robustness Check/Extension**
  - A common and instructive robustness check in DiD papers is to test the **pre-treatment trends** (the "falsification test").
  - **Replication:** Replicate the authors' analysis showing the estimated effect in the years *prior* to the regulation's implementation. If the DiD assumption holds, these pre-treatment coefficients should be statistically indistinguishable from zero.
- **Include a Writeup Explaining What the Robustness Check Achieves**
  - **Explanation:** The pre-treatment trend check directly tests the **Parallel Trends Assumption**. By estimating a non-effect in the periods before the policy was officially in place, the authors provide empirical evidence that the treatment and control groups were, in fact, following parallel trends just before the intervention. This bolsters confidence in the main result being a true causal effect of the policy change, rather than a result of pre-existing, differential trends.

Re-analyze

- **Re-analyze the Main Result using Methods Taught in this Class**
  - **Method Suggestion:** Use the **Inverse Probability Weighting (IPW) estimator** to re-analyze the main result.
  - The IPW method would involve estimating the propensity score (the probability of an area being treated) using covariates and then weighting observations by the inverse of their propensity score.
- **Justify Why these Methods Can be Applied to the Setting**
  - **Justification:** The IPW estimator is designed to handle selection bias in **observational studies** by creating a pseudo-population where the measured confounders (covariates) are balanced across the treatment and control groups.
  - In the context of the gasoline regulation, you would argue that the **Ignorability Assumption** holds *conditional on the set of observed covariates* (e.g., temperature, monitor location characteristics, time fixed effects) that determine which areas adopted the regulation when. The IPW method would thus directly address potential confounding factors that influence both the policy's placement and air quality.
- **Compare and Contrast Your Findings with the Main Result**
  - **Comparison:** Compare the IPW estimated treatment effect to the original DiD estimate.
  - **Discrepancy Analysis:** If your results differ significantly:
    - **Conjecture/Analysis:** Analyze if the difference is due to the IPW method providing a better **balancing** of observed covariates than the DiD fixed effects approach, or if the IPW result is simply more sensitive to the specification of the propensity score model. It could also suggest that the **functional form assumptions** (e.g., linearity) of the original DiD model were restrictive compared to the more flexible nature of IPW.