Evaluating the Effectiveness of Public Subsidies for Electric Vehicles

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Policy Evaluation Course

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Research Question and Motivation

Research Question: What is the causal impact of public subsidies on electric vehicle (EV) adoption?

Motivation:

- Climate change mitigation and decarbonization
- Public subsidies are widely used to encourage EV uptake
- Evaluating their true effectiveness is crucial for evidence-based policy

Why OLS is Not Enough

Model:

$$EV_t = \beta_0 + \beta_1 Subsidy_t + \gamma X_t' + \varepsilon_t$$

Problem: Endogeneity

- $Cov(X, \varepsilon) \neq 0$
- Subsidies may target regions already transitioning
- Omitted variable bias (e.g. environmental attitudes)
- Reverse causality

Conclusion: $\hat{\beta}_1$ from OLS is biased and not causal (but correlation).

OLS Estimator: addressing the sign of the bias

Consider the cost of electricity (CE_t). Studying the sign of the bias we get:

- **Positive correlation** between EV_t and $Subsidy_t \rightarrow \beta_1 > 0$
- **Negative correlation** between EV_t and $CE_t \rightarrow \gamma < 0$
- **Positive correlation** between CE_t and $Subsidy_t \rightarrow \delta > 0$

$(\gamma \times \delta) < 0$. The bias pushes the coefficient to the left (**lower bounded**).
The real β_1 is greater than the estimated $\hat{\beta}_1$.
$\rightarrow \hat{\beta}_1 < \beta_1 < \infty$

Ideal experiment

- **Population**: Turin's citizens
- **Unit of analysis**: individual $\rightarrow$ all those who are eligible to receive subsidies. (i.e. based on income)
- **Random assignment**: each individual must be randomly assigned to a group (treatment (T) and control (C) group). $D = E[EV^T|T] - E[EV^C|C]$

We don't have any selection bias since the population assignment to each group is random.

What About Regression Discontinuity Design (RDD)?

When applicable:

- If policy is based on a sharp cutoff (Income $<$ 30,000€)
- Compare units just above and just below the threshold

Pros:

- Strong causal identification *near the cutoff*

Cons:

- Effect is very local, not generalizable
- Requires detailed data and assumption of no manipulation

Model Specification (Fuzzy RDD)

Running variable: Income (I)
Outcome: Y_i = probability of purchasing an EV.
Cutoff: $I = 30,000$ €

Model:

$$Y_i = \alpha + \rho D_i + f(I_i - 30,000) + \varepsilon_i$$

- $D_i = 1$ if income $\leq 30,000 \rightarrow$ eligible for subsidy
- $f(\cdot)$ is a flexible function (e.g., linear or quadratic)
- ρ estimates the causal effect of the subsidy

Objective: Estimate the causal effect of receiving the EV subsidy near the income cutoff (ISEE = 30,000 €) using a Fuzzy Regression Discontinuity Design.

Fuzzy RDD: 2SLS Model with Polynomial Controls

First Stage:

$$T_i = \pi_0 + \pi_1 D_i + \pi_2 (I_i - c) + \pi_3 (I_i - c)^2 + u_i$$

This stage estimates how eligibility (based on income cutoff) affects the probability of actually receiving the subsidy.

Second Stage:

$$Y_i = \alpha + \tau \hat{T}_i + \beta_1 (I_i - c) + \beta_2 (I_i - c)^2 + \varepsilon_i$$

This stage uses the predicted subsidy receipt to estimate the causal effect on the probability of purchasing an EV.

Fuzzy RDD

- The **first stage** checks whether the cutoff significantly changes the likelihood of receiving the treatment.
- The **second stage** uses this variation to estimate the treatment's causal impact.
- We are identifying the **causal effect** for those individuals whose treatment status is influenced by the cutoff — the *compliers*.

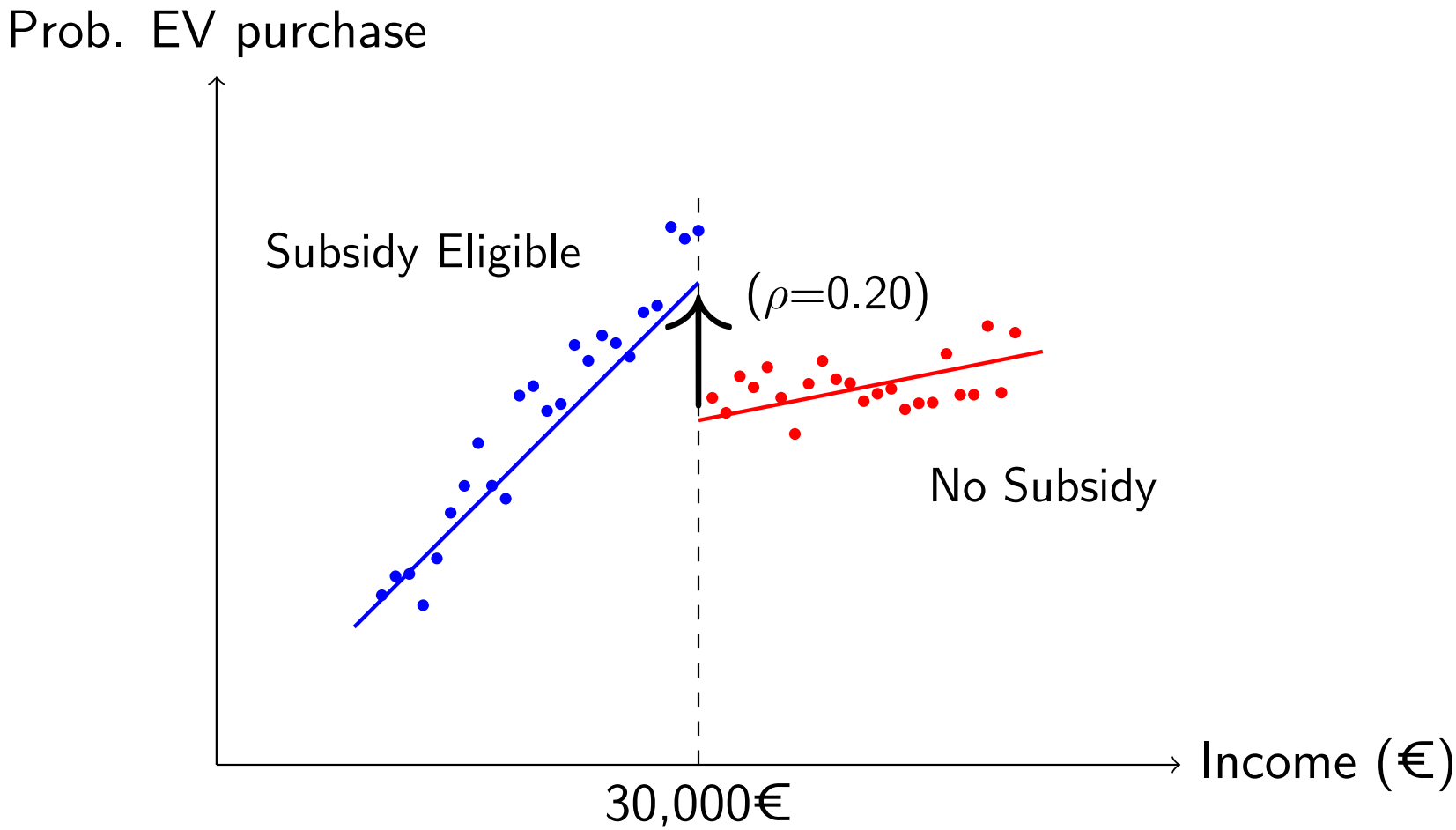
Takeaway: Fuzzy RDD with 2SLS allows us to isolate the true causal effect even when assignment to treatment is not perfectly sharp.

Simulated Example (RDD)

- Data on individuals with an income around the 30,000 € threshold
- Below threshold: sharp increase in purchases due to subsidy eligibility
- Above threshold: lower adoption rate

Estimated effect: $\hat{\rho} = 0.20 \rightarrow 20$ percentage point increase in probability of purchase due to subsidy

Regression Discontinuity Design (RDD): Visualization



Other Estimation Methods

Method	Strengths	Examples
IV	Solves endogeneity via exogenous variation	Use party vote share to predict subsidy exposure
DiD	Simple, intuitive; compares treatment and control over time	Compare Piemonte and Lombardia before/after policy
FE	Controls for time-invariant unobservables in panel data	Use panel data of regions over years with EV sales

Conclusions

Key Findings

- **Effectiveness of subsidies:** Public subsidies significantly increase the adoption of electric vehicles, especially in regions with strong policies and good charging infrastructure.
- **Consumer behavior:** The effectiveness of subsidies is strongly influenced by consumer awareness of environmental issues and the perceived immediate economic benefit.
- **Environmental impact:** Subsidies contribute to reducing emissions, but the overall impact depends on the widespread adoption of electric vehicles in the long term.

Conclusions

Challenges in Policy Implementation

- **Cultural and behavioral resistance:** Some consumers may be reluctant to change their mobility habits, despite economic incentives.
- **Inadequate charging infrastructure:** A lack of accessible charging points limits the adoption of electric vehicles, even with subsidies in place.
- **High production costs:** Subsidies may not be sufficient to significantly reduce the cost of electric vehicles in the long run.
- **Fiscal sustainability:** Financing subsidies may place pressure on public budgets, particularly in times of economic hardship.

Policy Recommendations

- A comprehensive strategy should include long-term investments in charging infrastructure, consumer education, and ongoing support for producers.
- It is crucial to complement subsidies with policies aimed at reducing the production cost of electric vehicles, such as research and development incentives for manufacturers.
- A broader societal shift towards sustainable transportation will require addressing behavioral barriers and promoting environmental consciousness.