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A Comprehensive Impact Evaluation Framework for EERE's Small Business and Startup Investment

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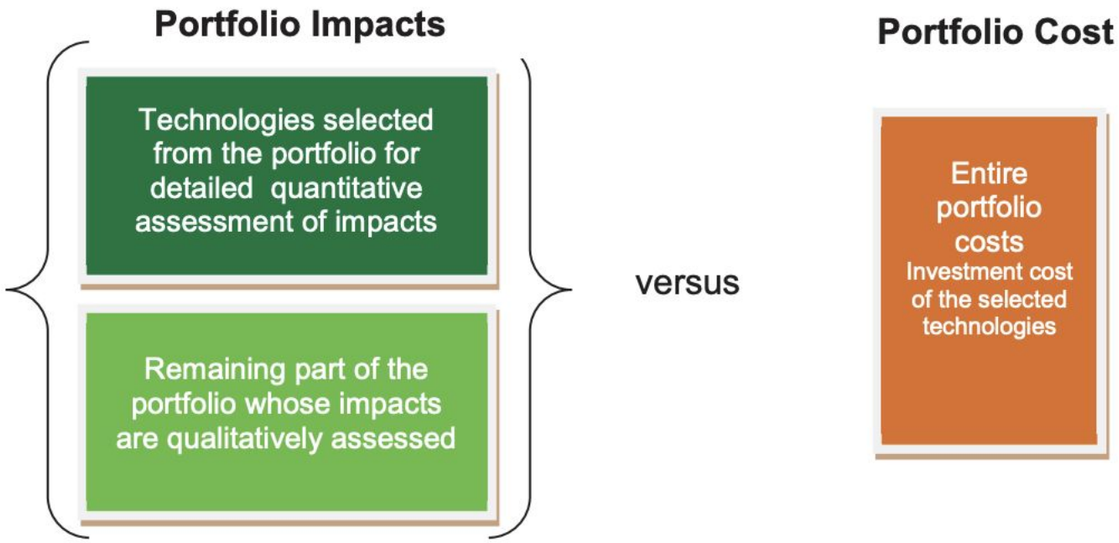
Background

- Investments in research and development (R&D) made by the federal government play a critical supporting role in America's economic growth
- The U.S. Department of Energy's (DOE's) Office of Energy Efficiency and Renewable Energy (EERE) invests in a broad range of R&D projects in transportation, energy efficiency, and renewable energy sources to address challenges and gaps in technology development
- These federal investments aim to promote new technological advances, as well as stimulate and enable the private sector to accelerate the transfer of research into commercial technologies.

Summary of Prior Impact Evaluation Literature

- To date, DOE's EERE has conducted 7 impact evaluation studies of R&D investment over various technologies
- Since 2014, these impact evaluation studies have followed DOE's Standard Impact Evaluation Methodology
- This methodology requires a portfolio approach which selects a few projects from within a portfolio for detailed evaluation
  - Calculates economic (and other) benefits compared to total portfolio R&D



Note: "portfolio" is entire program, subprogram, or other grouping to be studied

Source: Rosalie Ruegg, TIA Consulting

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Limitations of Prior Impact Evaluations

- Established framework used to estimate key metrics such as net economic benefits, benefit to cost ratios, or return on investment for R&D investments in advanced energy technologies

- Methodologies are necessarily technology-specific (require a “next best technology” for a counterfactual)
  - Requires expert judgment & ultimately a selection of the next best technology to compute results (non-experimental design)
- Portfolio approach used for cost effectiveness reasons can lead to limited/judgmental sampling of technologies
- The portfolio approach also calculates economic (and other) benefits compared to total portfolio R&D, which can result in conservative B/C ratios
- However, comparing R&D costs may not be equivalent to the costs a firm incurs to bring a technology to market, which could result in optimistic B/C ratios
- Sensitive to assumptions such as expected useful life, discounting, and how benefits are defined and measured
- 4 of the 7 studies are greater than 10 years old and all 7 studies are greater than 5 years old

Objective

- We propose an impact evaluation framework to assess how EERE's regular financial assistance awards (SBIR, STTR, and other investments) drive innovation, grow small business, and support regional and national economic growth
  - Our impact evaluation framework will consider best practices and needed improvements from prior EERE impact evaluations
  - Our framework is a quasi-experimental econometric design leveraging techniques from the program evaluation literature to determine the causal effect of EERE's awards
  - Our framework leverages PNNL's vast EERE technology tracking data as well as fundamental financial and market data from proprietary databases.
    - ✔ A data driven approach to impact evaluation
    - ✔ Our intention is to provide a holistic assessment of financial assistance awards on firm innovation, growth, and other measures

Impact Evaluation: An Econometrics Point-of-View

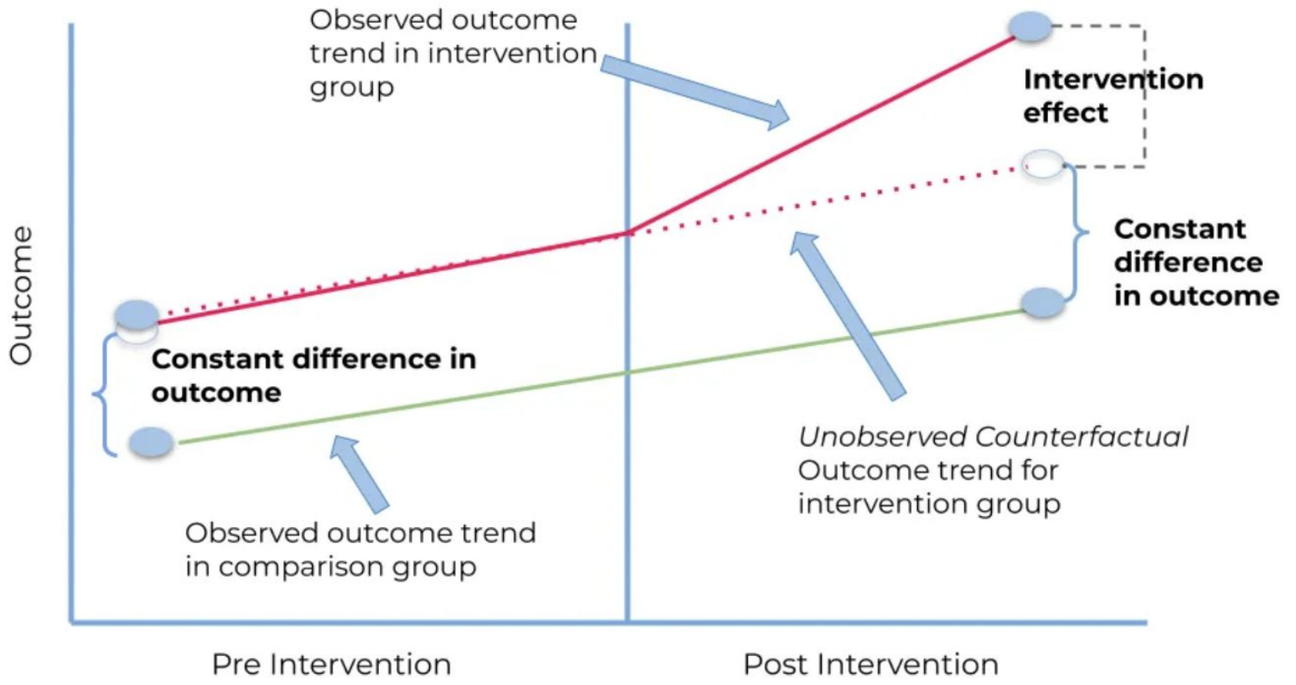
- In econometric analysis, impact evaluation falls under the umbrella of program evaluation
  - Concerned with the estimation of causal effects of interventions
  - Interventions referred to as “treatments”
  - The intervention in our impact evaluation framework is the DOE EERE’s federal investments in R&D (regular financial awards SBIR, STTR, and other investments)

- Why use econometrics?
  - Rigorous, data-driven approach to understanding the effects of policies and interventions. Can estimate the causal impact of an intervention, controlling for other factors that might also influence the outcome.

See Imbens and Wooldridge (2009) or Abadie and Cattaneo (2018) for surveys of the literature

Impact Evaluation: Difference-in-Differences

- Quasi-experimental method
- Assesses the impact of an intervention by measuring the change in outcome across comparison groups between a pre- and post-intervention (treatment) period
- Requires an assumption of parallel trends



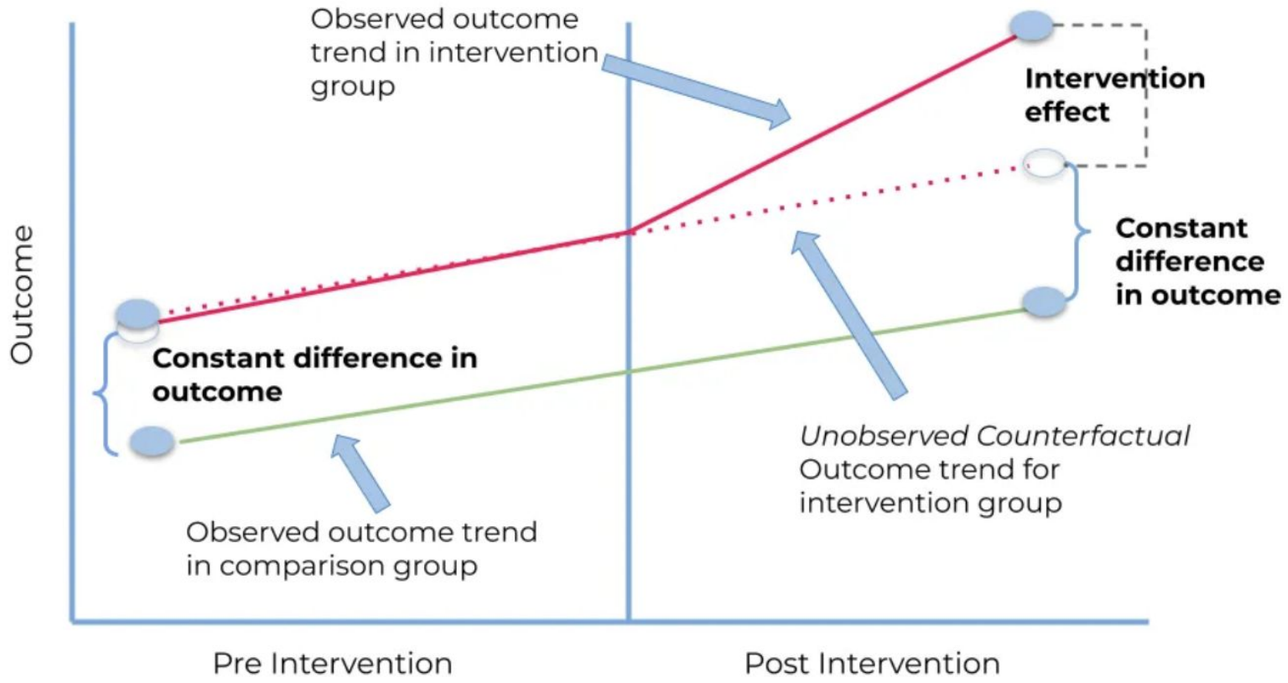
$$Y = \beta_0 + \beta_1 Treatment + \beta_2 Post + \delta \text{Treatment} * \text{Post} + \epsilon$$

Figure Source: https://www.publichealth.columbia.edu/research/population-health-methods/difference-difference-estimation

Challenge: How to Choose the Right Control Group?

- Challenge: We don't observe the potential outcome of a firm's R&D impact (innovation, growth, etc.) *had they not received the award*

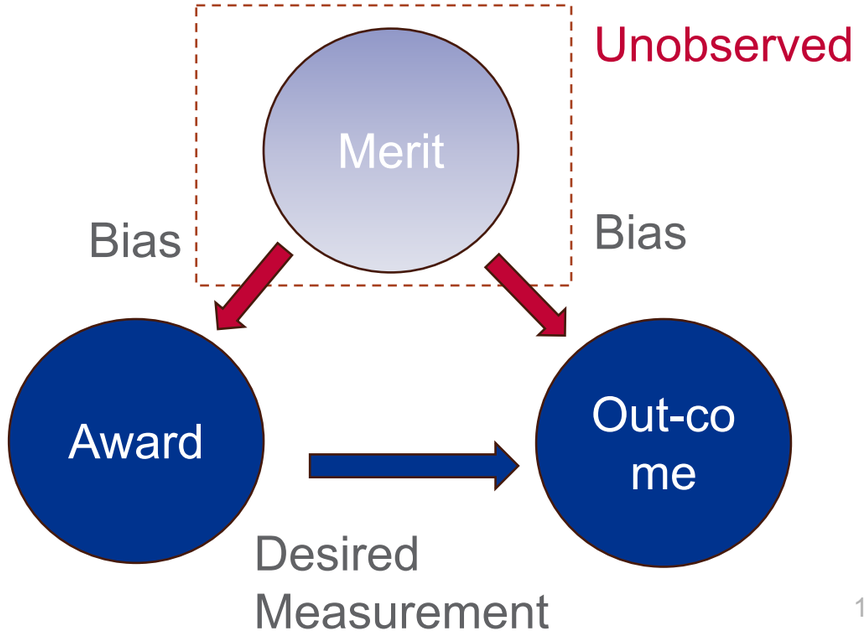
Construct a control group from non-awarded firms to estimate this unobserved potential outcome



See Imbens and Wooldridge (2009) or Abadie and Cattaneo (2018) for surveys of the literature

Challenge: Treatment is Not Random

- The U.S. Department of Energy selects candidates based on merit
  - It is plausible that even without funding, firms that were awarded could be more successful than other firms
  - In econometrics this is selection bias or “selection into treatment”



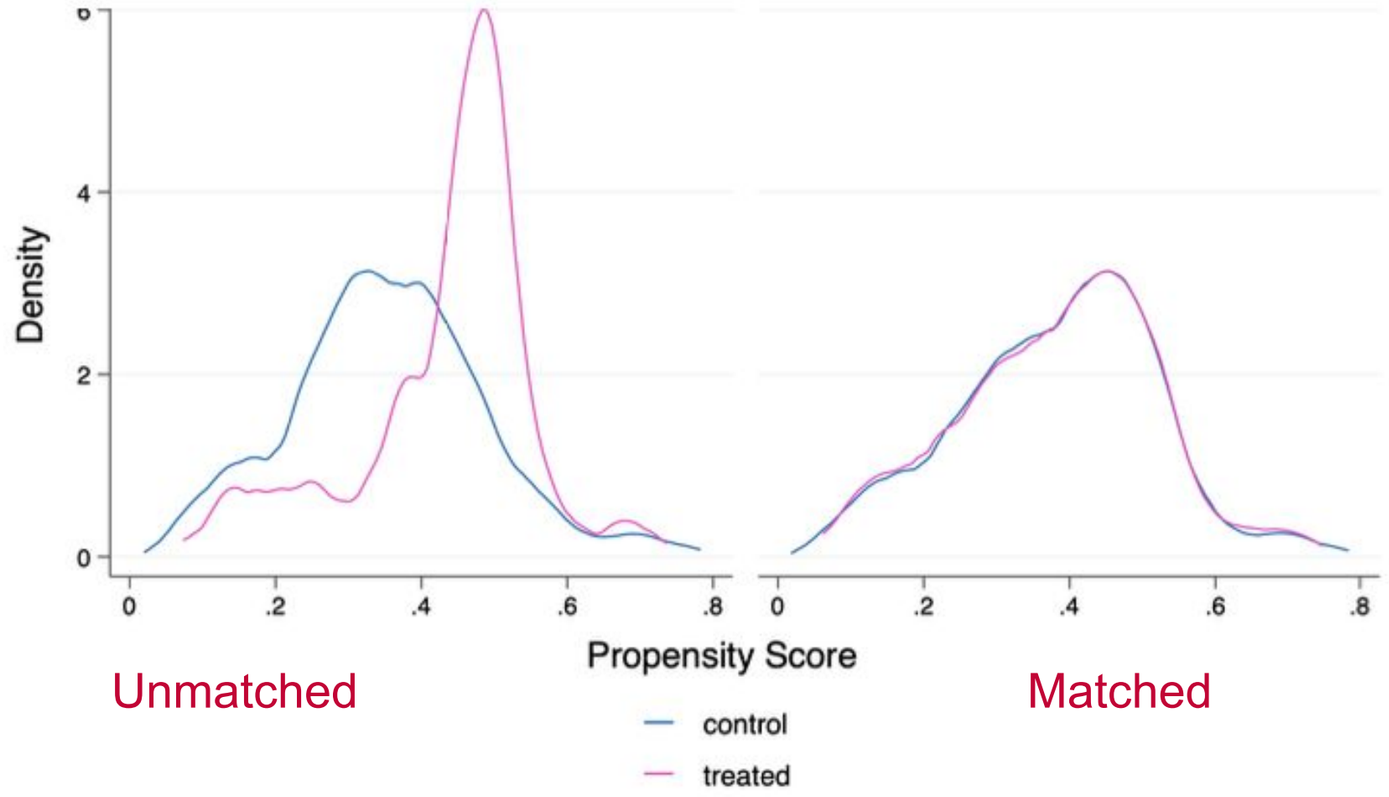
- Can use matching methods: well matched treatment and control samples can reduce bias

→ Try to replicate a “randomized experiment” (as close as possible) by choosing treatment and control groups that have similar covariate distributions

- Can also use instrumental variable approaches

Challenge: Treatment is not Random

- Identification of causal effects using matching methods:
  - Propensity to receive treatment



Challenge: Treatment Spillovers

- Key identifying assumption for causal inference – assumes that treatment received by one firm does not affect outcomes for another firm
  - Stable Unit Treatment Value Assumption (SUTVA)
- Award funding could have these types of general equilibrium effects, if, for example, technological innovation has “spillover effects”
  - Example: Herd immunity from vaccines

- Potentially, redefine the unit of interest, i.e., an industry instead of a firm
- Or, can model the interactions directly, i.e. model treatment spillovers

Challenge: Dynamic Treatment Effects

- Treatment effects may change over time, for example, award funding may have more impact in later years than award year
- To analyze this impact, we can use several methods which analyze both staggered treatment and treatment over time:
  - Method: limit the set of effective comparison units to “clean controls” that were not previously treated or by controlling for dynamic treatment effects
    - ✔ Cengiz et al. (2019) build a new dataset for each treated cohort containing only not-yet treated controls, and stack them into a larger dataset for regression analysis
    - ✔ Callaway and Sant’Anna (2019) construct weighted averages of all valid 2X2 treated vs. untreated comparisons
    - ✔ Wooldridge (2021) suggests an OLS regression that flexibly controls for dynamic treatment effects by treated cohort, which produces results similar to Callaway and Sant’Anna, with smaller standard errors

Impact Evaluation Next Steps: Data Collection

- Potential outcome variables of interest: subsequent revenue and employment, follow-on investment, patents and citations, survival or M&A
- Matching variables of interest: firm characteristics including firm industry, firm age, employment size, sales and asset histories, locational variables, potentially pre-treatment outcomes
  - **Next steps**: Our team recently received the data and can now do a deeper dive on firms that received an award to understand potential award decisions, leveraging PNNL's unique insights from tech tracking where possible

Impact Evaluation Next Steps: Perform Our Comprehensive Approach to Impact Evaluation

- We will identify and construct a control group of firms that were not selected for a financial assistance award
- We will pre-process the data with matching on covariates (firm characteristics) that are important to applying for a financial award and may influence outcomes
- We will then estimate the treatment effect (impact) of financial assistance awards using difference-in-difference estimators on the matched data
  - Can include newer methods to treat dynamic treatment effects as well staggered treatment timing
- Consider robustness to selection bias, treatment spillovers, etc.
- Consider other methods

Combining designs helps to replicate the experimental outcome (i.e., regression methods on a balanced sample reduces bias, Imbens and Wooldridge, 2009)

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Thank you

Appendix: Additional Econometric Methods

- Instrumental variables approach to address selection bias
  - Returns to education and returns to training programs could provide some insight into potential instruments
- Regression discontinuity
  - Models treatment effect based on rule variable with a cutoff. We require use the DoE scoring of the projects (currently a data limitation). The model fits a function (linear, polynomial etc.) to the rule variable, and estimates the discrete change in a function that happens at the cutoff