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Quantitative methods: Difference-in-differences and propensity score matching

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Abstract

Impact assessment serves as an essential approach for examining the social, economic, and behavioral effects of development programs and public policies. It helps policymakers and researchers determine whether specific interventions have successfully achieved their intended objectives, while also revealing any unintended or indirect outcomes.

Among the quantitative quasi-experimental methods, Difference-in-Differences (DiD) and Propensity Score Matching (PSM) are widely used techniques for estimating causal impacts in situations where randomization is not feasible. This paper explains the conceptual background, major assumptions, methodological procedures, and practical applications of both DiD and PSM. It presents two case studies one related to livestock extension and another focused on rural development to illustrate how these methods can be applied in real-world impact evaluation. The comparative discussion further demonstrates that combining DiD and PSM strengthens the validity, reliability, and overall credibility of impact assessment findings.

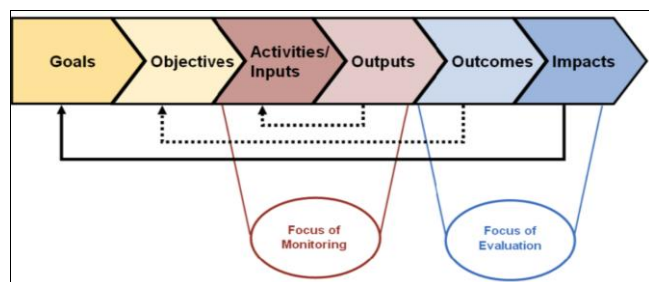
Keywords: Impact assessment, difference-in-differences, propensity score matching, quasi-experimental methods, livestock extension, rural development

Introduction

Impact assessment is a structured and systematic approach used to examine the social, economic, and behavioral changes that result from a specific program, policy, or project affecting individuals and communities (OECD, 2002) ^[10]. It enables policymakers, researchers, and development professionals to determine whether an intervention has successfully met its intended objectives while also identifying any unexpected or unintended effects that may have emerged during implementation (Becker, 2001) ^[4].

Furthermore, impact assessment strengthens accountability by ensuring that resources are used effectively and transparently. It promotes evidence-based decision-making, allowing governments and organizations to rely on empirical findings rather than assumptions when designing or modifying policies (Taylor, Bryan, & Goodrich, 2002). By systematically analyzing outcomes, it also contributes to refining the planning and implementation of future interventions.

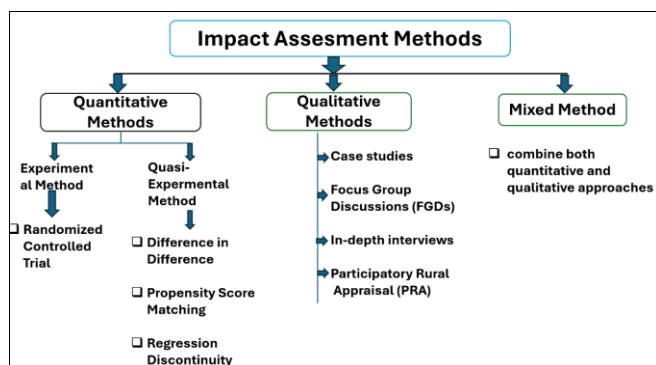
Significance of impact assessment extends beyond measuring results; it provides deeper insights into social consequences, enhances policy formulation and strategic planning, encourages active stakeholder participation, and supports long-term sustainability and social equity (Gertler *et al.*, 2016) ^[8].



Theoretical Background of Impact Assessment

Impact evaluation techniques are generally grouped into quantitative, qualitative, and mixed-method approaches. Quantitative approaches use numerical data and statistical tools to estimate the magnitude of change resulting from an intervention. In contrast, qualitative approaches focus on understanding people's perceptions, experiences, and social contexts through methods such as interviews, focus group discussions (FGDs), and participatory rural appraisal (PRA). Mixed-method designs integrate both quantitative and qualitative techniques to provide a more comprehensive and balanced understanding of program outcomes (Gertler *et al.*, 2016)^[8].

While experimental designs like Randomized Controlled Trials (RCTs) are considered the strongest method for establishing cause-and-effect relationships, they are not always practical or feasible in real-world development settings. In such situations, quasi-experimental methods particularly Difference-in-Differences (DiD) and Propensity Score Matching (PSM) offer reliable alternatives by enabling researchers to estimate causal impacts even in the absence of random assignment.

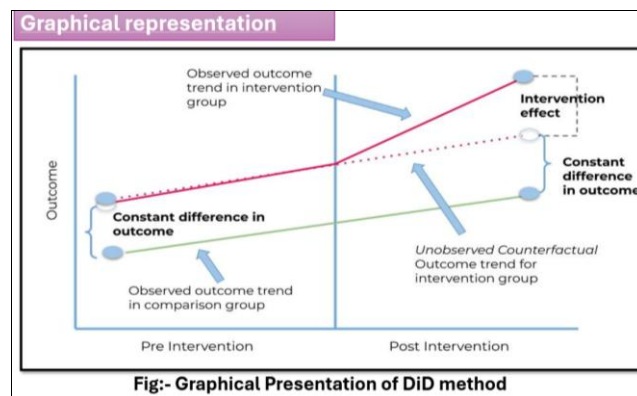


Difference-in-Differences (DiD) Method

The Difference-in-Differences (DiD) method estimates the causal impact of an intervention by comparing changes in outcomes over time between a treatment group (affected) and a control group (unaffected). It isolates the treatment effect by removing time-invariant unobserved heterogeneity (Angrist & Pischke, 2009)^[2]. The method assumes that, in the absence of treatment, both groups would have followed parallel trends in outcomes. This assumption is critical for unbiased estimation. Mathematically, the DiD estimator is expressed as:

$$DiD = (Y_{T,after} - Y_{T,before}) - (Y_{C,after} - Y_{C,before})$$

where Y_T and Y_C denote average outcomes for treatment and control groups, respectively (Bertrand *et al.*, 2004)^[5].



Key Features

- Examines Pre- and Post-Intervention Changes:** Evaluates how outcomes in the treatment group differ before and after the implementation of the program.
- Incorporates a Comparison Group:** Assesses the difference in changes between the treatment group and a control group that did not receive the intervention.
- Determines Causal Effect:** Aims to estimate the actual impact of a policy or program by isolating its specific contribution to observed changes.
- Assumes Similar Trend Patterns:** Relies on the assumption that, without the intervention, both treatment and control groups would have experienced comparable trends over time.
- Accounts for Constant Unobserved Characteristics:** Reduces bias by controlling for factors that remain unchanged across time, such as inherent abilities, land quality, or other fixed attributes.
- Requires Data from Multiple Time Periods:** Depends on panel data or repeated cross-sectional data collected at least before and after the intervention.
- Suitable When Random Assignment Is Not Feasible:** Particularly valuable in practical settings where conducting randomized controlled trials (RCTs) is not possible.

Case Study 1: Application of DiD in Livestock Extension

A livestock training program was introduced in two districts to enhance dairy farmers' productivity. District A received the training (treatment group), while District B did not (control group). Data on milk yield (liters/day) were collected before and after the intervention.

The average milk yield in District A increased from 8 to 12 liters/day, while in District B, it rose from 7 to 8 liters/day due to natural improvement. The DiD estimate is $(12-8) - (8-7) = 4 - 1 = 3$ liters/day, indicating the program led to an average increase of 3 liters per cow per day. This finding demonstrates that farmer training and improved management practices significantly boost productivity.

Livestock Training Program Impact on Milk Yield

District	Group	Before (Liters/day)	After (Liters/day)	Change
District A	Treatment (Training Provided)	8	12	+4
District B	Control (No Training)	7	8	+1

DiD Calculation Table

Component	Value
Change in Treatment Group	$12 - 8 = 4$
Change in Control Group	$8 - 7 = 1$
Difference-in-Differences (DiD)	$4 - 1 = 3$ liters/day

Policy Implication: This result suggests that continuous farmer capacity-building and extension interventions can substantially improve dairy output and income. However, ensuring similar pre-intervention conditions and monitoring for external factors such as feed prices or disease outbreaks is crucial for accuracy.

Advantages of Difference-in-Differences (DiD)

- 1. Eliminates Bias from Fixed Characteristics:** The method helps reduce bias arising from characteristics that remain constant over time, such as individual ability, geographic location, or inherent group traits.
- 2. Straightforward and Practical Approach:** DiD can be implemented using standard regression techniques and does not require highly complex statistical procedures.
- 3. Does Not Require Random Assignment:** It is particularly useful in real-world settings where conducting randomized controlled trials (RCTs) is impractical or impossible.
- 4. Controls for Shared External Events:** When both treatment and comparison groups experience the same external shocks (for example, droughts or economic changes), the method effectively accounts for their influence.
- 5. Broad Range of Applications:** DiD is widely applied across disciplines such as economics, public policy, public health, agriculture, social sciences, and livestock research to estimate causal impacts.

Limitations of Difference-in-Differences (DiD)

- 1. Depends on the Parallel Trends Assumption:** The validity of results relies on both groups exhibiting similar trends before the intervention. If this assumption is violated, the estimates may be biased.
- 2. Does Not Address Time-Varying Unobserved Factors:** If unexpected changes affect one group differently over time, the estimated impact may be distorted.
- 3. Requires Pre-Intervention Data:** Accurate application demands information from both before and after the program; without baseline data, the method cannot be properly used.
- 4. Highly Sensitive to Control Group Selection:** Choosing an inappropriate comparison group can lead to misleading or inaccurate conclusions about program impact.
- 5. May Confound Effects of Concurrent Policies:** If other interventions occur simultaneously, DiD may incorrectly attribute their effects to the primary program being evaluated.

Propensity Score Matching (PSM) Method

Propensity Score Matching (PSM), first developed by Rosenbaum and Rubin (1983)^[11], is a quantitative method used to estimate causal relationships in studies where random assignment is not possible. The technique aims to create comparability between treated and untreated groups by matching individuals who share similar characteristics based

on a calculated propensity score. This score reflects the likelihood that a unit receives the treatment, given a set of observed variables, and is commonly estimated through logistic regression analysis.

Several matching procedures are applied within the PSM framework, including Nearest Neighbor, Caliper, Radius, and Kernel matching methods (Caliendo & Kopeinig, 2008)^[6]. Once matching is completed, researchers conduct balance tests to ensure that the covariates are similarly distributed across groups. The treatment effect is then determined by comparing the outcomes of the matched treated and control units (Austin, 2011)^[3].

Key Features

- 1. Creates Comparable Groups Based on Observed Factors:** PSM constructs treatment and comparison groups that are similar in measurable characteristics such as age, education, income, or herd size, thereby reducing selection bias.
- 2. Relies on Propensity Scores:** Each participant is assigned a probability of receiving the intervention based on observed variables, and matching is performed using this estimated probability.
- 3. Adjusts Only for Measured Variables:** The method corrects for bias arising from observable covariates but cannot account for unmeasured or hidden factors.
- 4. Suitable for Cross-Sectional Data:** Unlike Difference-in-Differences, PSM does not require data from multiple time periods and can be applied to data collected at a single point in time.
- 5. Estimates the Average Treatment Effect on the Treated (ATT):** The approach calculates the impact of the intervention specifically for participants who received it by comparing them with similar non-participants.
- 6. Minimizes Selection Bias:** By matching individuals with comparable baseline characteristics, PSM improves the fairness and validity of comparisons between treated and untreated groups.
- 7. Offers Multiple Matching Techniques:** Researchers can select from various matching procedures depending on study requirements, including Nearest Neighbor, Radius (Caliper), Kernel, and Stratification methods.
 - a. Nearest Neighbor Matching (NNM):** This approach matches each treated unit with the control unit that has the closest propensity score. It is straightforward and commonly applied; however, if no close match exists, the quality of pairing may be weak.
 - b. Radius (Caliper) Matching:** This method establishes a predefined maximum distance (caliper) between propensity scores. A treated unit is matched only with control units within this acceptable range, reducing the risk of poor matches.
 - c. Kernel Matching:** Instead of selecting a single control, this technique uses weighted averages of multiple control units. Units with propensity scores closer to the treated unit receive higher weights, while those further away receive lower weights. This approach often lowers variance and yields smoother impact estimates.
- 8. Highly Applicable in Non-Experimental Settings:** PSM is particularly valuable in studies where random assignment is not feasible, especially in fields such as social sciences, agriculture, livestock research, and public policy evaluation.

Case Study 2: PSM in a Rural Development Program

Case Study: Evaluating the Impact of Dairy Training Program Using Propensity Score Matching (PSM)

Sector: Livestock / Dairy Extension

Method: Propensity Score Matching (PSM)

Objective: To measure the true impact of a dairy training program on milk yield by reducing selection bias.

1. Background of the Study

A dairy development agency launched a Dairy Management Training Program for smallholder farmers.

The goal was to improve:

- Feeding practices
- Housing management
- Milking hygiene
- Animal health care

Not all farmers participated—those who joined were generally more educated, progressive, and had better farm resources.

Therefore, direct comparison of participants vs. non-participants would be biased.

To remove this bias, PSM was applied.

2. Research Question

“Does the dairy training program significantly increase milk yield among trained farmers compared to similar untrained farmers?”

3. Data Collection

Data collected from 400 dairy farmers:

- 200 trained (treatment group)
- 200 untrained (control group)

Variables collected

Type	Variables
Outcome variable	Daily milk yield (liters/day)
Covariates (baseline characteristics)	Age, education, herd size, breed type, experience, access to veterinarian, feed availability
Treatment variable	Participation in training (Yes/No)

4. Step 1 — Estimate the Propensity Score

A logistic regression model was used:

$$P(T = 1 | X) = \text{logistic}(\alpha + \beta X)$$

Where:

T = Training participation

X = Covariates

This model calculates the probability that a farmer *would* participate in training based on characteristics.

5. Step 2 — Matching Technique

Farmers were matched using:

Nearest-Neighbor Matching (1:1, with replacement)

Each trained farmer was matched with one untrained farmer with the closest propensity score.

Matching caliper = 0.05 to avoid poor matches.

6. Step 3 — Balance Checking

After matching:

- Standardized mean differences between groups were reduced (<10%).
- Covariates became statistically similar.

This confirmed good balance and reduced selection bias.

7. Step 4 — Average Treatment Effect on the Treated (ATT)

After matching

Average Milk Yield (liters/day)

Group	Mean Yield
Trained farmers	11.8
Matched untrained farmers	9.6

ATT Calculation

$$ATT = 11.8 - 9.6 = 2.2 \text{ liters/day}$$

8. Interpretation

The Dairy Training Program increased milk yield by 2.2 liters/day per cow, after removing selection bias.

This improvement was due to:

- Better feeding (balanced ration)
- Improved shed hygiene
- Correct milking technique
- Timely deworming and vaccination

9. Policy Implications

- Training programs are effective and should be scaled to other districts.
- More focus on feed management training gives higher gains.
- Extension workers should target farmers with low baseline productivity—they benefit most.

10. Conclusion

PSM helped in:

- Removing selection bias
- Creating a comparable control group
- Accurately estimating the program's impact

The dairy training significantly improved milk productivity, proving that training-based extension programs are crucial for livestock sector development.

Advantages of Propensity Score Matching (PSM)

- 1. Minimizes Selection Bias:** By pairing treated individuals with non-treated individuals who share similar characteristics, PSM helps create a more comparable control group.
- 2. Adjusts for Measurable Characteristics:** The method accounts for observable variables such as age, education, income, herd size, and other relevant factors, thereby improving the precision of impact estimates.
- 3. Does Not Require Random Assignment:** PSM is especially useful in observational studies where randomization cannot be implemented, making it practical for real-world program evaluations.
- 4. Applicable to Single-Period Data:** Unlike some other causal methods, PSM can be applied to cross-sectional datasets and does not require information from multiple time points.
- 5. Provides Multiple Matching Options:** Researchers can choose from various matching procedures—such as

Nearest Neighbor, Kernel, or Radius matching—based on the nature of the data and research objectives.

Limitations of Propensity Score Matching (PSM)

1. **Fails to Address Unobserved Variables:** The technique can only adjust for variables that are measured; hidden or unrecorded factors may still introduce bias.
2. **Highly Dependent on Selected Covariates:** If key explanatory variables are omitted, the quality of matching weakens and the estimated effects may become unreliable.

3. **Needs Adequate Sample Size:** Effective matching requires a sufficiently large dataset; small samples may result in poor or imprecise matches.
4. **Potential Loss of Observations:** Units that cannot be properly matched are excluded from the analysis, which can reduce sample size and statistical power.
5. **Results May Vary by Matching Technique:** Different matching approaches (such as Nearest Neighbor, Kernel, or Radius) can yield different estimates, potentially affecting the stability of conclusions.

Comparison Between DiD and PSM

Point	Difference-in-Differences (DiD)	Propensity Score Matching (PSM)
Purpose	Measures impact using before–after data of treatment and control groups	Measures impact by matching similar individuals based on covariates
Data Requirement	Requires panel data (before and after)	Works with cross-sectional data (one time point)
Controls for	Controls for time-invariant unobserved factors automatically	Controls for observable characteristics only
Key Assumption	Parallel trend assumption must hold	Conditional independence (selection on observables) must hold
Bias Reduction	Reduces bias from fixed differences between groups	Reduces bias from confounding due to observed covariates

Conclusion

Impact assessment plays a crucial role in promoting evidence-based planning and informed decision-making, particularly in the fields of agriculture and rural development. It enables policymakers, researchers, and development practitioners to systematically evaluate whether programs and policies achieve their intended objectives and generate meaningful improvements in livelihoods and community well-being.

In situations where random assignment is not feasible, analytical approaches such as Difference-in-Differences (DiD) and Propensity Score Matching (PSM) offer strong and practical alternatives for estimating causal effects. The DiD approach focuses on measuring changes over time and helps control for unobserved factors that remain constant, while PSM enhances comparability by constructing statistically similar treatment and control groups based on observed characteristics.

When these two methods are applied together, they complement each other's strengths and address individual limitations, thereby improving the robustness, credibility, and overall reliability of impact findings. Such integrated approaches provide deeper and more comprehensive insights, ultimately supporting better policy formulation, improved program design, and sustainable development outcomes.

Conflict of Interest

Not available

Financial Support

Not available

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