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THEORY, PREMISES AND EMPIRICAL RELATION: DIFFERENCE-IN-DIFFERENCE IN POLICY DESCISIONS

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Abstract

When determining the efficiency of welfare programs, development initiatives and public policies impact evaluation of such is important. Impact evaluation measures the casual relationship between the dependent and independent variable. In impact evaluation estimates can be experimental or quasi experimental. Experimental studies are not possible everywhere due to its financial and logistical constraint, so quasi experimental studies plays a vital role there. One of the quasi experimental technique of impact evaluation is Difference-in-Difference .The Difference-in-Difference (DID) approach has become one of the most popular quasi-experimental methods for estimating causal effects in non-experimental settings. A treatment group exposed to a policy intervention and a control group that is not impacted by the intervention are compared for changes in outcomes over time using the DID method. The approach accounts for common time trends that impact both groups and unobserved factors that remains constant over time by concentrating on differences across both time and groups. In the context of impact evaluation, this paper offers a thorough analysis of the DID approach. It covers the method's conceptual framework, mathematical formulation, fundamental presumptions, and real-world application. Additionally, a fictitious example of how DID uses interaction terms in a regression framework to estimate treatment effects is presented in the paper. Also, a critical analysis of the DID approach's advantages and limitation is discussed. The review emphasizes that although DID offers an effective and user-friendly tool for evaluating the impact for policies, its validity is primarily dependent on the satisfaction of crucial presumptions like the parallel trend assumption. The relevance of DID in current empirical research and its value in assessing development interventions are highlighted in the paper's conclusion.

Keywords: Impact evaluation, DID, Parallel trend, quasi experimental, Empirical research, Policy decisions.

Introduction:

Many initiatives are carried out by governments and development organisations with the goal of enhancing social and economic results.

For that reason Impact evaluation is now a important part of program and policy evaluation and in taking public policy decision. Effective policy design and resource allocation depend on determining whether these interventions truly have the desired effects. Randomized controlled trials (RCTs) are not possible in many real-world scenarios because of financial, logistical and ethical drawbacks. Because of this, researchers frequently use quasi-experimental techniques that use observational data to approximate experimental conditions. The Difference-in-Difference (DID) approach is one of these techniques that have become very popular.

By comparing the change in outcomes over time between participants (treatment group) and with non-participants (control group), the DID estimates the causal relationship of a policy intervention. The main concept is that the method removes biases resulting from time-invariant unobserved factors by looking at differences across time and groups. Numerous disciplines, including education policy, labor economics, health economics, and development economics, have made extensive use of DID in their study.

DID methodology is conceptually reviewed in this paper. The aim is to describe the method's theoretical underpinnings, provide its mathematical formulation, go over the presumptions needed for accurate estimation, and highlight its limitations and advantages with respect to impact assessment.

Difference-in-Difference (DID) :

The Difference-in-Difference method is a quasi-experimental econometric technique used to measure the causal effect of a policy or a program. The Difference-in-Difference method involves measuring the change in the outcome variable over time for two groups:

1. Treatment group: the group that is exposed to the intervention.

2. Control group: the group that is not exposed to the intervention.

The basic idea behind the Difference-in-Difference method is that if there is a change in the outcome variable for the control group, this change indicates the overall change that would have happened even without the intervention. Hence, by subtracting the change in the outcome variable for the control group, the Difference-in-Difference method aims to measure the causal effect of the intervention.

The Difference-in-Difference method involves two differences:

1. Difference over time (i.e., before and after the intervention).

2. Difference between the two groups (treatment and control).

DID Model: Statistical Regression Equation:

DID model is applied in economic research in a regression equation having an interaction term and the coefficient of the interaction term is the impact of the intervention.

The Regression is equation is,

$$y_t = \beta_0 + \beta_1 D_{1i} + \beta_2 D_t + \beta_3 (D_{1i} * D_t) + u_t$$

Where,

Symbol	Description of the symbol
i	Individual i
y_t	Dependent variable/Outcome variable measured at time period "t"
β_0	Intercept term (Baseline outcome for the control group in the pre-treatment period)
β_1	Coefficient measuring the mean difference between the treatment group and control group (Before intervention)
D_{1i}	Treatment dummy variable (D_{1i} = 1 :Treatment group & D_{1i} = 0: Control group)
β_2	Coefficient capturing the overall time effect common to both treatment and control group
D_t	Time dummy variable (D_t = 1: Post treatment & D_t = 0: Pre treatment)
$(D_{1i} * D_t)$	Interaction term between treatment and time variables capturing the treatment effect post intervention.
u_t	Error term (Unobserved factors affecting the dependent/outcome variable)

Interpretation of the Interaction Term:

The interaction term, i.e., (Treat * Post), is very important in DID estimation because it shows the change in the outcome for the treatment group after the intervention compared to the control group.

Interpretation:

β1 shows the baseline difference between treatment and control groups.

β2 shows the common time trend in both groups.

β3 shows the causal effect of policy intervention, and thus it is the DID estimator.

DID Regression Equation: An illustration

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Group	Time	Outcome (y)	Treatment Dummy (D_{1i})	Time Dummy (D_t)	Interaction Term ($D_{1i} * D_t$)
Control	Before	4300	0	0	0
Control	After	4700	0	1	0
Treatment	Before	4500	1	0	0
Treatment	After	6000	1	1	1

Here as per the above table,

$\beta_0 = 4300$ (Control Group before intervention)

$\beta_0 + \beta_2 = 4700$ (Control Group after Program), so $\beta_2 = 400$ (Time effect)

$\beta_0 + \beta_1 = 4500$ (Treatment group before program), so $\beta_1 = 200$ (Group difference)

$\beta_0 + \beta_1 + \beta_2 + \beta_3 = 6000$ (Treatment group after program), so $\beta_3 = 1100$

Putting all the values of β in the DID regression equation,

$$y_t = 4300 + 200D_{1i} + 400D_t + 1100(D_{1i} * D_t) + u_t$$

Here, $\beta 3 = 1100$

Difference-in-Differences estimate (causal impact of program)
So the program increased household consumption by ₹1100 on average.

Assumptions of DID Model

For DID to produce unbiased causal results, certain conditions must be satisfied.

1) **Parallel Trend Assumption:**

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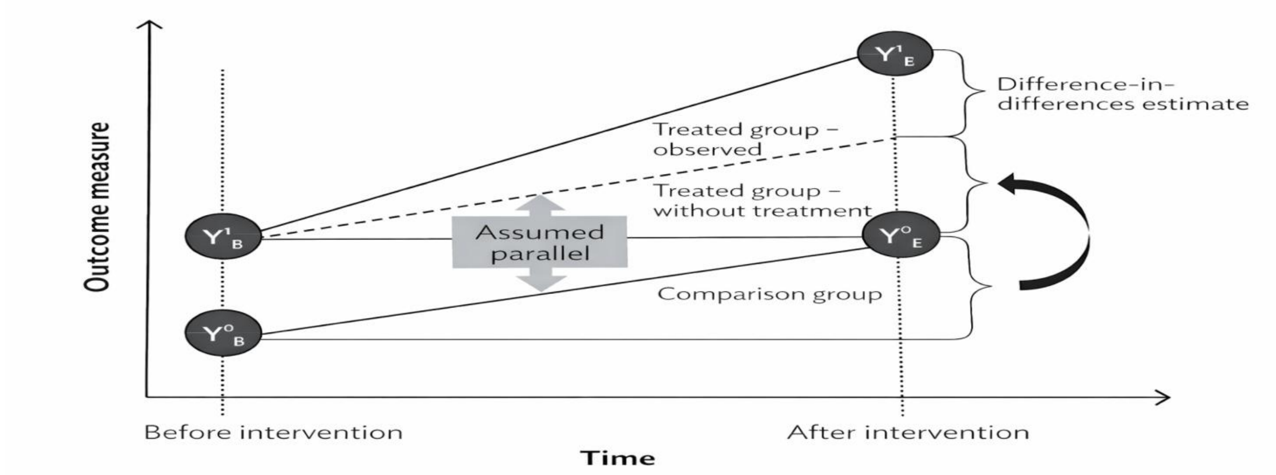
The most important assumption for DID is the parallel trend assumption. This assumption holds that, in the absence of any policy intervention, the trend for the treatment and control groups would have been similar.

Figure-1: Parallel Trend Assumption of Treatment and Control group



Where,

$\mathbf{Y^1_B}$ – Outcome of treated group **before** intervention

$\mathbf{Y^1_E}$ – Outcome of treated group **after** intervention

$\mathbf{Y^0_B}$ – Outcome of control group **before** intervention

$\mathbf{Y^0_E}$ – Outcome of control group **after** intervention

In other words, the gap between the two groups would have remained constant in the absence of any policy intervention.

2) **No Simultaneous Confounding Policies:**

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There must not be any policy changes or shocks that affect only the treatment group during the sample period. If such policy changes occur, they might influence the results.

3) **Stable Composition of Groups:**

The composition of the treatment and control groups must not change significantly. If there is a significant change in the composition of groups, this might influence the results.

4) No Spillover Effects:

The control group must not be indirectly influenced by any policy intervention in the treatment group. Spillover effects might influence the results for the treatment and control groups.

Merits of DID Applications in Impact Evaluation :

The advantages of the Difference-in-Difference method in empirical studies are as follows:

1. It helps control for unobserved heterogeneity: The DID method helps control for biases due to unobserved heterogeneity, which is constant over time.

2. It is simple and intuitive: The DID method is simple and easy to interpret.

3. It can be applied to observational data: The DID method can be applied even if randomized experiments are not feasible.

4. It is widely used for policy evaluation: The DID method is widely used for policy evaluation, including labor market policies, education policies, health policies, and social welfare policies.

5. It has a flexible regression framework: The DID method has a flexible regression framework, enabling the inclusion of control variables.

Demerits of DID Applications in Impact Evaluation:

However, the DID method have some limitations, some of which are discussed below:

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1) Dependence on parallel trend assumption: If the parallel trend assumption is not met, then the DID method may not yield the correct result.

2) Sensitivity to policy shocks: The occurrence of other policy shocks during the period may affect the result.

3) Data requirements: The DID method requires data to be available both before and after the intervention. This may not always be possible.

4) Spillover effects: If the control group is indirectly affected, then the DID method may not yield the correct result.

5) Measurement errors: If the outcome variables are not measured correctly, then the result may not be correct.

Conclusion:

This paper examined the conceptual and empirical bases of the Difference-in-Differences methodology as an essential tool for causal impact evaluation in applied economics and policy analysis. The study discussed the theoretical framework of the DiD methodology and its application for estimating treatment effects by exploiting differences over time between treated and control groups. It also provided an illustration of the statistical regression equation and the interaction term that are used by the DID estimator to capture the program effect, accounting for baseline differences and time trends.

The hypothetical case used in the analysis served to further explain the practical application of the method, as well as how the interaction term used in the regression framework works to account for the causal effect of a program or policy intervention. This, therefore, demonstrates the strength of the DID method in offering a transparent estimate of treatment effects, even without the need for randomized experiments.

The explanation of the core assumptions underlying the DID method, as seen in the discussion of the parallel trends assumption, served to emphasize the need for specific conditions to be met for the method to yield causal effects. Although the method has some advantages, such as simplicity, interpretability, and flexibility, it has some limitations that need to be addressed appropriately.

In conclusion, the "Difference-in-Differences" method, as a quasi-experimental approach, still enjoys significant application in the evaluation of public policies and socio-economic programs. The extension of this method into the realm of regression analysis makes it an important tool for empirical research in the field of development economics. Further extensions and refinements to the "DID" method, such as the application of additional datasets, heterogeneous effects, and the extension of the method into the realm of matching methods, can only serve to improve its overall efficiency as a tool for policy evaluation.

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