Difference-in-Differences Regression Model and Comparable Methods

Randall E. Schumacker
University of Alabama

Todd Sherron
Texas State University

Multiple regression model applications have expanded since the 1960s, especially with the development of computers and computer software. The Difference-in-Differences regression model has received much attention in determining treatment effects between experimental and control groups. There are two other regression applications that are comparable models in analyzing treatment effects. The other two similar applications are regression-discontinuity and test of slope differences; sometimes referred to as a test of parallelism. This article presents the similarity between these regression applications, which is a test of interaction between the group variable and a continuous variable (time; scores) that usually involves a cut-off point before and after a treatment condition. The treatment effect is shown to be the same in all three methods.

Multiple regression model applications have expanded since the 1960s, especially with the development of computers and computer software. Today, textbooks, journal articles, conference papers and the Internet explore applications related to ordinary least squares, repeated measures, multi-level, logit, and logistic regression methods (e.g. Pedhazur, 1997; Agresti, 1996). Publications in journals have expounded the many different applications of multiple regression models and issues affecting their analyses (e.g. Newman, Schumacker & Walker, 2014; www.glmj.org). The Internet contains multiple websites on these regression topics.

A multiple regression application, *difference-in-differences regression model* (DiD)is used to assess the treatment effect when comparing an experimental group to a control group. The DiD model estimates the differential impact of a treatment on subjects in an experimental group versus a control group, generally over time in a pre-test/post-test research design. DiD can assess the data from a randomized control trial that tests the efficacy of a medical treatment (Machin & Fayers, 2010). The concept of "treatment" can also include a study of minimum wage effects on restaurants, impact of natural disasters in a state on housing prices or opening of a new airline route on passenger tickets. The unit of analysis would be the subject, restaurant, state, or airline. The dependent variable would be whether a subject received treatment or not, whether restaurants that changed their minimum wage had a different employment level than restaurants that did not change their minimum wage, states housing prices with a natural disaster compared to states housing prices without a natural disaster, or a comparison of passenger ticket sales between an airline that opened a new route versus an airline with an existing route between two cities.

The *DiD regression model* includes a key variable, time, in the analysis. The passage of time will change the value of the dependent variable from pre-treatment to post-treatment in a research study. The DiD regression model accounts for the effect of time, thus allowing for interpretation of the treatment effect on the dependent variable over and above the passage of a time effect in the study. A *regression discontinuity* (RD) model also incorporates a pre-treatment to post-treatment over time regression model.

The RD model assesses when the regression line "discontinues" hence the term discontinuity. The test of *slope differences* (SD) in a regression model can also incorporate a pre-treatment to post-treatment effect over time to test regression coefficient differences between the slope of the two regression lines (experimental group and control group). A Google™ search on the Internet for "Difference-in-Differences Regression Model" yields multiple websites with applications using different software packages. A Google™ search on the Internet for "Regression Discontinuity Design Model" also yields multiple websites with applications using different software packages. Finally, a Google™ search on the Internet for "Test of Slope Differences" yields applications with different software packages.

The DiD model, RD model, and SD model are compared using `R` software. The `R` program code for each application is in the Appendix. The similar regression equations and how data are analyzed will be presented. The interpretation of results and graphical display will illustrate the similarity of the regression methods. Although named differently, each regression method analyzes the treatment effect via an interaction term.

Regression Methods

Difference-in-Differences Method

The difference-in-differences (DiD) linear regression equation includes the parameters for the *time*, *treatment* (experimental vs control) and a *time* by *treatment* interaction. The equation can be expressed as:

$$Y_i = \beta_0 + \beta_1 * \text{Time}_i + \beta_2 * \text{Treatment}_i + \beta_3 * (\text{Time} * \text{Treatment})_i + \epsilon_i$$

where:

Y is the dependent variable
β_0 is the intercept parameter
β_1 is the time parameter (time is dummy coded 0 or 1 for pre or post)
β_2 is the treatment parameter (treatment is dummy coded 0 or 1 for ctrl or treatment grp)
β_3 is the interaction parameter (multiply time and treatment dummy coded values)
ϵ_i is the error term that indicates all factors not represented in model

The DiD model is presented as analyzing four different equations. The regression equations are based on the 2 x 2 matrix of dummy coded variables for time and treatment. These four equations are shown in Table 1.

The DiD regression equations permit differences in pre-treatment and post-treatment as well as pre-control and post-control subjects. The expected difference effect (E) for the pre-treatment and post-treatment group is expressed as:

E(Time-1, Treatment = 1) – E(Time = 0, Treatment = 1) =
$(\beta_0 + \beta_1 + \beta_2 + \beta_3) - (\beta_0 + \beta_2) = \beta_1 + \beta_3$

For the control group, the pre-control and post-control expected difference effect (E) is expressed as:

E(Time-1,Treatment = 0) – E(Time = 0, Treatment = 0) =
$(\beta_0 + \beta_1) - (\beta_0) = \beta_1$

In the DiD method, the difference between the experimental and control groups yields β_3, the net effect of the treatment in the experimenttal group. This is expressed as:

E(DiD Effect) = $(\beta_1 + \beta_3) - \beta_1 = \beta_3$

The DiD method computes four means for the combinations of treatment (0,1) and control (0,1) groups. A simple calculation yields the β_3 regression coefficient:

β_3 = (d – c) – (b – a)

where:
a = mean (pre-control [0]; pre-treatment [0])
b = mean (pre-control [0]; post-treatment [1])
c = mean (post-control [1]; pre-treatment [0])
d = mean (post-control [1]; post-treatment [1])

Table 1. DiD Regression Equations

	Time = 0	Time = 1
Treatment = 0	$Y_i = \beta_0 + \epsilon_i$	$Y_i = \beta_0 + \beta_1 + \epsilon_i$
Treatment = 1	$Y_i = \beta_0 + \beta_2 + \epsilon$	$Y_i = \beta_0 + \beta_1 + \beta_2 + \beta_3 + \epsilon_i$

Table 2. Earned Income Credit

	post93 = 0	*post93* = 1
anykids = 0	$Y_i = \beta_0 + \epsilon_i$	$Y_i = \beta_0 + \beta_1 + \epsilon_i$
anykids = 1	$Y_i = \beta_0 + \beta_2 + \epsilon$	$Y_i = \beta_0 + \beta_1 + \beta_2 + \beta_3 + \epsilon_i$

DiD Data Analysis Example

The data set used for the DiD data analysis was obtained from the following website:
https://github.com/CausalReinforcer/Stata/blob/master/eitc.dta

The data includes the earned income credit for women with more than one child (treatment variable). This treatment variable was recoded to a dummy coded variable, *anykids*, where a*nykids* = 1 indicated women with one or more children and *anykids* = 0 for women with no children. The year variable was dummy coded into *post93*= 0 and *post93* = 1 where *post93* = 1 indicated the years 1994 to present when earned income credit was created by the IRS. The regression equations for the different combinations of treatment and control are in Table 2.

The R code for the DiD treatment effect of earned income credit is presented in the Appendix. The DiD method yielded the following four group combination means to compute the DiD Effect.

a = .57545
b = .44596
c = .57338
d = .49076

The DiD effect is:

DiD Effect = (d – c) – (b – a)
= (.49076-.57338) – (.44596-.57545)
= **0.04687**

The DiD treatment effect can be displayed as illustrated in Figure 1.

The DiD treatment effect can be calculated by including an interaction term in the DiD regression equation. The `R` code that includes the interaction term (*post93:anykids*) is expressed as:

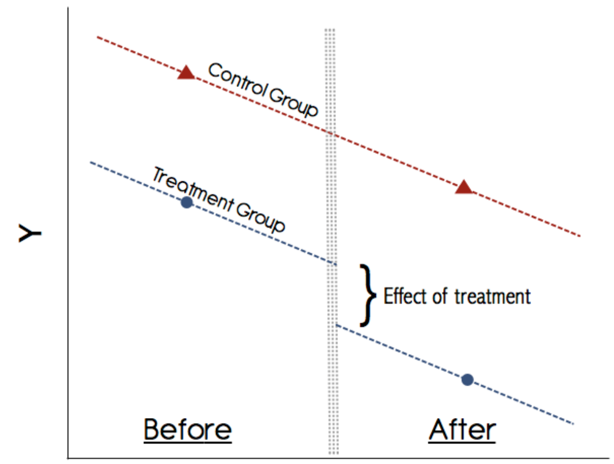

Figure 1. Difference-in-Differences Treatment Effect

```
options(scipen = 999)
eitc.result = lm(work ~ post93 + anykids + post93:anykids,data=eitc)
summary(eitc.result)
```

The results are shown as:

```
Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     0.575460   0.008845  65.060  < 2e-16 ***
post93         -0.002074   0.012931  -0.160  0.87261
anykids        -0.129498   0.011676 -11.091  < 2e-16 ***
post93:anykids  0.046873   0.017158   2.732  0.00631 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Note: DiD Effect = $\boldsymbol{\beta_3}$ (post93:anykids) = 0.04687

The DiD treatment effect is the same as the estimate for the interaction term (boldfaced). The interaction parameter's *t*-test and *p*-value indicate if the DiD treatment effect is statistically significant. The standard error term permits a 95% confidence interval around the parameter estimate. The statistical results yielded the same DiD treatment effect as the calculations using the combination of group means.

Regression-Discontinuity Method

The regression-discontinuity (RD) model assesses the treatment effect around an assignment variable. RD is generally used in a quasi-experimental design that measures the impact of an intervention or treatment. It is a popular regression application in evaluation of programs where a true experimental design is not applicable. The program treatment is designated as occurring before (control group) or after (treatment group) a defined cut-off point (assignment variable) as shown in Figure 2a.

The understanding of a "counterfactual" regression line aids in the understanding of the RD treatment effect. The "counterfactual" regression line indicates the trend if no treatment. This is displayed in Figure 2b.

RD Data Analysis Example

The data set used for the RD data analysis was obtained from the following website:
https://ds4ps.org/pe4ps-textbook/docs/p-060-reg-discontinuity.html

The regression discontinuity design is predicting student's performance (grade) based on class attendance (centered variable to median cut-off), and a dummy coded group variable where attendance lower than median was assigned to treatment group and students who had attendance greater than the median assigned to control group. The basic research question was: Does a mandatory attendance policy increase student final grade performance? The data analysis should reflect whether a mandatory attendance policy increased the performance (grades) of students enrolled in the treatment group.

The variables are:

Performance: Final exam grade (0 - 100)
Treatment: Dummy coded (1 = treatment; 0 = control)
Attendance: (Percent of class attendance – 0% to 100%)
Attendance – Centered: (Percent attendance centered around median percent)

RD data analyses are calculated using similar regression equations to the DiD regression equation:

$$Y_i = \beta_0 + \beta_1 * Treatment_i + \beta_2 * Attendc_i + \beta_3 * (Treatment * Attendc)_i + \epsilon_i$$

The RD effect can be calculated by including an interaction term in the regression equation. The `R` code is in the Appendix. The `R` program code that includes the interaction term is expressed as:

```
options(scipen=999)
RDout = lm(Perf ~ Trt + Attendc + Trt*Attendc, data = RD)
summary(RDout)
```

The results are shown as:

```
Coefficients:
             Estimate Std. Error t value    Pr(>|t|)
(Intercept)  69.6357     1.7689  39.367     0.000000018 ***
Trt          -1.5058     3.2775  -0.459     0.66210
Attendc       0.9983     0.1958   5.099     0.00222 **
Trt:Attendc  -0.6126     0.3124  -1.961     0.09760 .
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Note: $\beta_3(Trt{:}Attendc)$ = -0.6126 (Would be the same in DiD calculations)

The results indicated that there was no statistical difference between the treatment and control groups (β_1); there was a difference in attendance (β_2) as expected, but no statistical difference in groups by attendance interaction (β_3). The treatment effect was not statistically significant, so there was no difference in the group's regression slope values at the cut-off point. If β_3 had been significant, then a treatment effect (regression line discontinuity) would have appeared in Figure 2a. Of course, we could calculate the four means for the combinations of treatment and attendance, but the difference calculations would yield the same β_3 = -0.6126 result.

Slope Differences Method

The slope differences (SD) method is simply comparing the slopes of the regression lines for two groups. The regression lines if parallel would have different intercept values but the same slope values. When two slope coefficients are different, a one-unit change in a predictor is associated with different mean changes in the response variable. In Figure 3a, a one-unit increase in *Input* is associated with a greater increase in *Output* in *Condition B* than in *Condition A*. We can *see* that the slopes look different but is this difference statistically significant.

A comparison of regression slopes is simply an interaction term as noted in the DiD and RD analysis before. We would include an interaction term (*Input* * *Condition*) in the regression equation to test whether the slopes of the two groups are statistically significantly different.

The regression equation would be:

$$Y_i = \beta_0 + \beta_1 * Input_i + \beta_2 * Condition_i + \beta_3 * (Input * Condition)_i + \epsilon_i$$

The `R` program code for the regression equation is:

```
SDout = lm(Output ~ Input + Condition + Input * Condition)
summary(SDout)
```

The results are indicated as:

```
Coefficients:
                   Estimate   Std. Error  t value   Pr(>|t|)
(Intercept)          9.099     0.98        9.29      0.000 ***
Input                1.535     0.082      18.67      0.000 ***
Condition B         -2.360     1.390      -1.70      0.093
Input:Condition B    0.469     0.116       4.03      0.000 ***
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

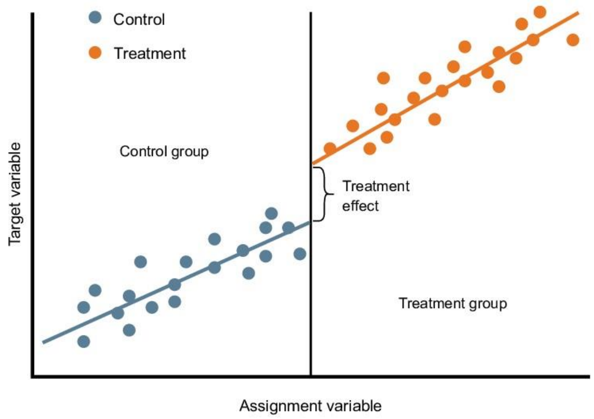

Figure 2a Regression Discontinuity

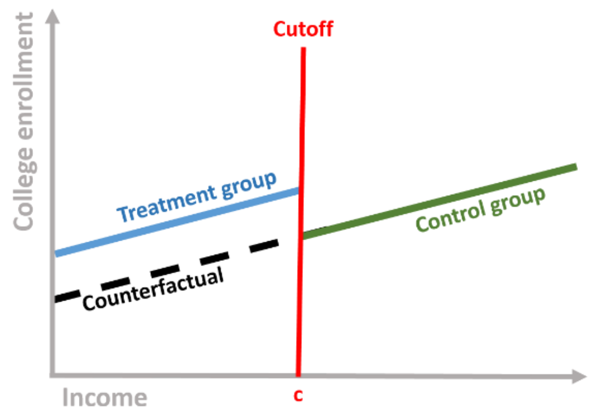

Figure 2b Counterfactual Regression Line

The interaction coefficient β_3 (Input:Condition) = 0.469 was statistically significant (t = 4.03, p < .0001) which indicated that there was a statistically significant slope difference as depicted in Figure 3a.

Another data analysis example illustrates when regression line slopes are parallel (similar). This is depicted in Figure 3b. The *Iris* data set is included in the `R` software and the program code is included in the Appendix. The variable SpeciesID was declared numeric and only two species selected for comparison.

The `R` program code for the regression equation is:

```
out=lm(Petal.Length ~ Sepal.Length+SpeciesID+Sepal.Length*SpeciesID,data=iris2)
summary(out)
```

The results indicated:

```
Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)               -0.66559    1.71194  -0.389   0.6983
Sepal.Length               0.55925    0.28002   1.997   0.0486 *
SpeciesID                  0.42535    0.65854   0.646   0.5199
Sepal.Length:SpeciesID     0.06361    0.10573   0.602   0.5488
```

The interaction coefficient β_3 (Sepal.Length:SpeciesID) = 0.06361 was not statistically significant (t = 0.602, p =.5488) which indicated that the slopes were similar as depicted in Figure 3b. The results would be similar to DiD and RD analyses.

Comparison of All Three Methods

We used different data sets from the Internet to illustrate that the three methods are prevalent and depicted as being different. To avoid skeptics when using different data sets, we used the same data set to show that all estimated treatment effect values were the same via an interaction term. JMP® Pro 15.1.0 was used with the following data to compute the results. The dataset appears in the Appendix.

Difference-in-Differences Method

The DiD method computes four means for the combinations of treatment (0,1) and control (0,1) groups. A simple calculation yields the β_3 regression coefficient: The DiD effect is: β_3 = (d – c) – (b – a) where:

a = mean (pre-control [0]; pre-treatment [0])
b = mean (pre-control [0]; post-treatment [1])
c = mean (post-control [1]; pre-treatment [0])
d = mean (post-control [1]; post-treatment [1])

Mean	Mean Estimate	SD	N
a	51.0000	34.17	8
b	44.5714	27.18	7
c	48.7142	37.74	7
d	57.8750	31.11	8

Parameter Estimates

β_3 = (d – c) – (b – a)
β_3 = (57.8750 – 48.7142) – (44.5714 – 51.0000)
β_3 = (9.1608) – (-6.4286)
β_3 =15.58

The four cell means are also given by computing the unstandardized predicted Y values (PRE_1) in SPSS shown in Figure 4.

Regression-Discontinuity Method

The regression-discontinuity (RD) model assesses the treatment effect around an assignment variable. RD is generally used in a quasi-experimental design that measures the impact of an intervention or treatment. The program treatment is designated as occurring before (control group) or after (treatment group) a defined cut-off point (assignment variable).

Parameter Estimates

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq	Lower CL	Upper CL
Intercept	46.64	8.15	22.12	<.0001*	30.13	63.15
Group[0]	1.14	7.89	0.02	0.8849	-14.84	17.12
Time[0]	3.21	7.89	0.16	0.6844	-12.77	19.19
G*T	**15.58**	22.33	0.48	0.4869	-29.62	60.79

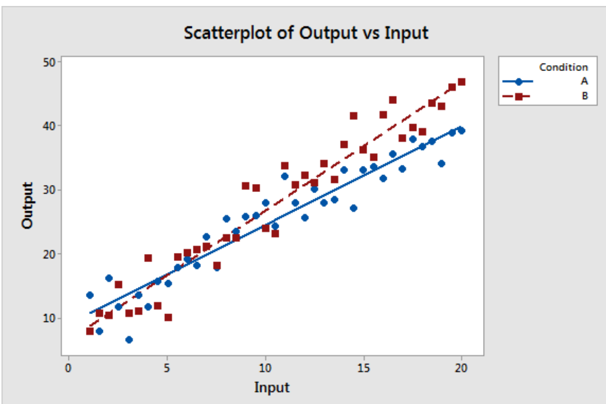

Figure 3a. Slope Differences (Interaction)

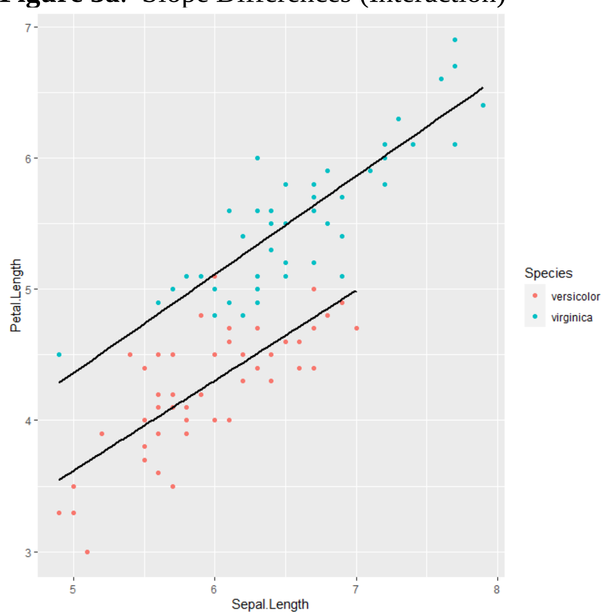

Figure 3b. Slope Differences (No Interaction)

Group	Time	Y	Interact	PRE_1
0	0	78	0	51.00000
0	0	42	0	51.00000
0	0	91	0	51.00000
0	0	15	0	51.00000
0	0	63	0	51.00000
0	0	3	0	51.00000
0	0	27	0	51.00000
0	0	89	0	51.00000
0	1	55	0	44.57143
0	1	5	0	44.57143
0	1	36	0	44.57143
0	1	70	0	44.57143
0	1	18	0	44.57143
0	1	47	0	44.57143
0	1	81	0	44.57143
1	0	9	0	48.71429
1	0	58	0	48.71429
1	0	22	0	48.71429
1	0	97	0	48.71429
1	0	69	0	48.71429
1	0	2	0	48.71429
1	0	84	0	48.71429
1	1	38	1	57.87500
1	1	74	1	57.87500
1	1	48	1	57.87500
1	1	31	1	57.87500
1	1	96	1	57.87500
1	1	12	1	57.87500
1	1	65	1	57.87500
1	1	99	1	57.87500

Figure 4. SPSS data

Slope Differences Method

The slope differences (SD) method is simply comparing the slopes of the regression lines for two groups. The regression lines if parallel would have different intercept values but the same slope values. When two slope coefficients are different, a one-unit change in a predictor is associated with different mean changes in the response variable.

Parameter Estimates

Term	Estimate	Std Error	L-R ChiSquare	Prob>ChiSq	Lower CL	Upper CL
Intercept	51.00	10.78	16.70	<.0001*	29.16	72.83
Group	-2.28	15.79	0.02	0.8849	-34.25	29.68
Time	-6.42	15.79	0.16	0.6844	-38.39	25.54
G*T	**15.58**	22.33	0.48	0.4869	-29.62	60.79

Summary

DiD	Regression Discontinuity	Slope Differences
β_3 =15.58	β_3 =15.58	β_3 =15.58

Conclusion

The difference-in-differences (DiD) regression method is typically used to estimate the effect of a specific intervention or treatment (drug study, program evaluation , disasters, etc.) by comparing the changes in outcomes over time between a population designated as the treatment group and a population that did not receive the treatment, a control or comparison group. The DiD regression model is prevalent in several academic fields, including econometrics, medicine, engineering, sociology, political science, etc., and conducted in many applications, e.g. program evaluation and public health. The general linear model (GLM) provides a simple straightforward approach to obtaining the DiD effect by estimating a coefficient for the interaction term.

The regression-discontinuity (RD) method, popular in evaluation quasi-experimental designs assesses the change in the regression line around a cut-off point. The treatment effect can be estimated by including an interaction term. This is essentially the same as in the DiD method. The slope differences (SD) method tests whether the slopes of two groups intersect or are parallel. The test of slope differences similarly includes an interaction term in the regression equation.

We have therefore shown that the DiD, RD, and SD methods are the same, and the treatment effect (group difference) is tested by including an interaction term in the general linear model. Robinson and Schumacker (2009) further discussed the issues around testing an interaction effect in regression. The GLM application has the benefit of providing a test of statistical significance and confidence intervals for the treatment effect regression coefficient. The GLM applications can also include time-varying parameters, non-linear parameters, and additional time points. A Google™ search indicated the prevalence of these methods across multiple websites. The general linear model (GLM) similarity has apparently been overlooked by researchers who treat these three methods as different.

We should note that the DiD example uses a continuous dependent variable with the two independent variables dummy coded [time (0,1) and treatment (0,1)]. The two dummy coded independent variables permitted the computation of means for the four cells, thus permitting the calculations for the treatment effect. We however showed that this amounted to a test of an interaction effect. The RD approach example had a continuous dependent variable with one continuous independent variable and a dummy coded treatment variable (0,1). The slope difference example likewise had a continuous dependent variable, one continuous independent variable and a dummy coded treatment variable (0,1). In the RD and slope difference examples this permitted the testing of the interaction effect.

Discussion

An important aspect of all three regression methods is the accounting for time. Time becomes a key variable in many quasi-experimental and experimental designs that involve pre and post testing with a comparison between subjects (or units of analysis) who received treatment and those who did not receive treatment. For example, Newman and Schumacker (2012) used a regression-discontinuity design in a medical setting to test treatment effectiveness. The design coding permitted examining treatment outcome differences in the intercept and slope over time. Schumacker and Holmes (2022) further explored whether the mean group difference tests in experimental designs masked the individual differences that are present in the regression analysis. They approached the design issue differently by including a separate regression equation for each subject. The subject's individual intercept and slope values were therefore tested and interpreted for change in the study.

The experimental design and model comparison approach is not new to research methods (Maxwell & Delaney, 2004). What has received increased attention over the years is the timing of events, time duration, and longitudinal data analysis (Singer & Willett, 1993; 2003). Researchers have become more aware of the effect of time on research outcomes in their research studies. The DiD regression modeling approach provides yet another perspective on how to analyze treatment data with a time component compared to RD and SD methods.

The difference-in-differences (DiD) regression method (Figure 1) is similar to the regression-discontinuity approach (Figure 2a) that has a treatment cutoff point and a regression model that tests slope differences (Figure 3a; Figure 3b), which all reflect a test of the interaction between time and treatment. The counterfactual in Figure 2b is obtained by assuming that the intervention (treatment) has not occurred (Treatment = 0), so that Y is only predicted by its relationship with X variable (Time; Score; or other continuous variable). For example, the regression equation setting Treatment = 0 is:

$$Y = \beta_0 + \beta_1 * 0 + \beta_2 * Score + e.$$

Therefore, The GLM model can also easily assess the counterfactual effect.

We used artificial intelligent ChatGPT to search for a comparison of the theory and assumptions for the three general linear model applications OpenAI. (2024). Therefore, we have added the results to the Appendix of this paper. Although we would agree the methods have some assumptions in common and possible theoretical differences, the fact remains they all have a test of an interaction effect for the treatment effect.

References

Agresti, A. (1996). *An Introduction to Categorical Data Analysis*. NY: John Wiley & Sons.

JMP® Pro 15.1.0 (2024). SAS Institute Inc., Cary, NC, 1989–2024.

Machin, D. & Fayers, P.M. (2010). *Randomized Clinical Trials: Design, Practice and Reporting*. Blackwell: Hoboken, New Jersey.

Maxwell, S.E. & Delaney, H.D. (2004). Designing Experiments and Analyzing Data: A Model Comparison Perspective (2nd Edition). Lawrence Erlbaum Associates, Mahwah: NJ.

Newman, I & Schumacker, R.E. (2012). Regression-Discontinuity Designs in Medical Settings: An Alternative to Quasi-Experimental Designs in Testing Treatment Effectiveness. *Multiple Linear Regression Viewpoints, 38*(1), 16-25.

Newman, I., Schumacker, R.E., & Walker, D. (2014). A Retrospective of 40 Years of MLRV Publication. *Multiple Linear Regression Viewpoints*, *40*(1), 1-4.

OpenAI. (2024). *ChatGPT* (3.5) [Large language model]. https://chat.openai.com

Pedhazur, E. (1997). *Multiple Regression in Behavioral Research* (3rd Edition). NY: Harcourt Brace College Publishers.

Robinson, C. & Schumacker, R.E. (2009). Interaction Effects: Centering, Variance Inflation Factor, and Interpretation Issues. *Multiple Linear Regression Viewpoints, Vol. 35(1), 6-11.*

Schumacker, R.E. & Holmes, L.F. (2022). Testing Individual vs Group Mean Differences in Social Science Research. *General Linear Model Journal*, *46*(1), 43 – 50.

Singer, J.D. & Willett, J.B. (1993). It's About Time: Using Discrete-Time Survival Analysis to Study Duration and the Timing of Events. *Journal of Educational Statistics*, 18(2), 155-195.

Singer, J.D. & Willett, J.B. (2003). *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence*. Oxford University Press: New York, NY.

Send correspondence to: Randall E. Schumacker
University of Alabama
Email: rschumacker@ua.edu

Appendices

References for Online Figures

Figure 1: https://stats.stackexchange.com/questions/564/what-is-difference-in-differences

Figure 2a: https://www.researchgate.net/figure/An-illustration-explaining-the-Regression-Discontinuity-Design-model-and-how-the-average_fig4_361733978

Figure 2b: https://ds4ps.org/pe4ps-textbook/docs/p-060-reg-discontinuity.html

Figure 3a: https://blog.minitab.com/en/adventures-in-statistics-2/how-to-compare-regression-lines-between-different-models

Figure 3b: Source: Iris data set in R

Dataset

```
0  0  78 0
0  0  42 0
0  0  91 0
0  0  15 0
0  0  63 0
0  0   3 0
0  0  27 0
0  0  89 0
0  1  55 0
0  1   5 0
0  1  36 0
0  1  70 0
0  1  18 0
0  1  47 0
0  1  81 0
1  0   9 0
1  0  58 0
1  0  22 0
1  0  97 0
1  0  69 0
1  0   2 0
1  0  84 0
1  1  38 1
1  1  74 1
1  1  48 1
1  1  31 1
1  1  96 1
1  1  12 1
1  1  65 1
1  1  99 1
```

Difference-in-Differences Regression Model R Code

```
# Difference in Difference Regression Model
# Earned Income Tax Credit on Females
# https://thetarzan.wordpress.com/2011/06/20/differences-in-differences-
estimation-in-r-and-#stata/

# Load the foreign package
require(foreign)

# Import data from web site
# update: first download the file eitc.dta from this link:
# https://github.com/CausalReinforcer/Stata/blob/master/eitc.dta
# Then import from your hard drive:

eitc = read.dta("C:/eitc.dta")
head(eitc, n=20)

# Create two additional dummy variables to indicate before/after
# and treatment/control groups.

# the EITC went into effect in the year 1994
eitc$post93 = as.numeric(eitc$year >= 1994)

# The EITC only affects women with at least one child, so the
# treatment group will be all women with children.
eitc$anykids = as.numeric(eitc$children >= 1)

# Compute the four means needed in the DID calculation:
a = sapply(subset(eitc, post93 == 0 & anykids == 0, select=work), mean)
b = sapply(subset(eitc, post93 == 0 & anykids == 1, select=work), mean)
c = sapply(subset(eitc, post93 == 1 & anykids == 0, select=work), mean)
d = sapply(subset(eitc, post93 == 1 & anykids == 1, select=work), mean)

# Compute the effect of the EITC on the employment of women with children:
DIDEffect = (d-c)-(b-a)
DIDEffect

>Work

0.046873
```

Regression-Discontinuity R Code

```
# Regression Discontinuity

# Data Set
# https://ds4ps.org/pe4ps-textbook/docs/p-060-reg-discontinuity.html
# Created comma-separated data set

RD = read.table("C:/Documents/AERA2024/grades.csv",header=FALSE,sep=",")
names(RD) = c("Perf","Trt","Attend","Attendc")
attach(RD)
RD

options(scipen=999)
RDout = lm(Perf ~ Trt + Attendc + Trt*Attendc, data = RD)
summary(RDout)
```

Slope Differences R Code

```
# Slope Differences Method
# Iris Data

attach(iris)
head(iris, n=10)

SpeciesID = as.numeric(iris$Species)
iris = data.frame (iris, SpeciesID)

iris2 = subset(iris, SpeciesID > 1)
iris2

out = lm(Petal.Length ~ Sepal.Length + SpeciesID +
Sepal.Length*SpeciesID,data=iris2)
summary(out)

library(ggplot2)

ggplot(iris2, aes(x=Sepal.Length, y=Petal.Length,color=Species)) +
geom_point() + geom_smooth(aes(group=SpeciesID), method=lm,
color='black',se=FALSE)
```

AI- ChatGPT

Command for ChatGPT (3.5): "Compare Differences in differences, regression discontinuity, and slope difference models using GLM in 15,000 words"

Comparing Difference-in-Differences (DID), Regression Discontinuity (RD), and Slope Difference Models using Generalized Linear Models (GLM) entails examining their theoretical foundations, methodologies, assumptions, applications, strengths, and limitations. Each of these methods addresses distinct research questions and scenarios, offering unique advantages and considerations in causal inference and policy evaluation. In this comprehensive comparison, we'll explore these aspects in detail to provide a nuanced understanding of their similarities, differences, and practical implications.

1. Theoretical Foundations:**

- **Difference-in-Differences (DID):** Rooted in the potential outcomes framework, DID compares the changes in outcomes over time between a treatment group and a control group, aiming to isolate the causal effect of an intervention or treatment.
- **Regression Discontinuity (RD):** RD leverages a sharp cutoff point in a continuous assignment variable to estimate causal effects near the threshold, assuming that individuals on either side of the cutoff are similar except for the treatment assignment, thus allowing for causal inference.
- **Slope Difference Models with GLM:** These models examine differences in slopes of regression lines between treatment and control groups, accommodating various distributional assumptions through GLM. They assess whether the rate of change in outcomes differs between groups over time.

2. Methodologies:**

- **Difference-in-Differences (DID):** DID typically employs linear regression or related methods to estimate treatment effects by differencing pre- and post-treatment outcomes between treatment and control groups while controlling for time-invariant confounders.

- **Regression Discontinuity (RD):** RD employs local linear or polynomial regression models to estimate treatment effects near the cutoff point, exploiting the discontinuity in the assignment variable to infer causal effects.
- **Slope Difference Models with GLM:** These models utilize GLM to estimate differences in slopes between treatment and control groups, allowing for flexible modeling of outcome distributions and accommodating non-linear relationships.

3. Assumptions:**

- **Difference-in-Differences (DID):** Key assumptions include the parallel trends assumption (that trends in outcomes would have been parallel in the absence of treatment) and no spillover effects between treatment and control groups.
- **Regression Discontinuity (RD):** Assumptions include the existence of a sharp cutoff in the assignment variable, continuity of potential outcomes around the cutoff, and no manipulation of the assignment variable near the threshold.

- **Slope Difference Models with GLM:** Assumptions encompass the existence of differential slopes between treatment and control groups, absence of unmeasured confounders, and correct specification of the outcome distributional form in GLM.

4. Applications:**

- **Difference-in-Differences (DID):** Widely used in policy evaluation, economics, and social sciences to assess the impact of interventions, reforms, or treatments on outcomes such as employment, wages, education, and health.
- **Regression Discontinuity (RD):** Commonly applied in program evaluation, education, economics, and public policy to evaluate the effects of eligibility thresholds, incentives, or interventions on outcomes such as educational attainment, income, and health.
- **Slope Difference Models with GLM:** Applied in various fields, including healthcare, social sciences, and epidemiology, to analyze longitudinal data and assess changes in outcome trajectories over time between different groups, accommodating diverse outcome distributions.

5. Strengths and Limitations:**

- **Difference-in-Differences (DID):**
  - **Strengths:** Allows for causal inference from observational data, straightforward implementation, and robustness to time-invariant confounders.
  - **Limitations:** Relies on the parallel trends assumption, susceptible to unobserved time-varying confounders, and may yield biased estimates if assumptions are violated.
- **Regression Discontinuity (RD):**
  - **Strengths:** Offers credible causal inference near the threshold, exploits natural experiments, and provides local average treatment effects.
  - **Limitations:** Limited generalizability beyond the cutoff, susceptibility to manipulation around the threshold, and potential extrapolation concerns.
- **Slope Difference Models with GLM:**
  - **Strengths:** Flexible modeling of outcome distributions, accommodates non-linear relationships, and allows for robust inference on changes in slopes.
  - **Limitations:** Requires careful consideration of distributional assumptions, potential model misspecification, and interpretation challenges for complex models.

6. Practical Considerations:**

- **Data Requirements:** Each method may have specific data requirements, such as the availability of pre- and post-treatment data for DID, continuity of assignment variable for RD, and longitudinal data for slope difference models.
- **Model Complexity:** The complexity of implementation and interpretation varies across methods, with DID being relatively straightforward, RD requiring careful design around the threshold, and slope difference models with GLM offering flexibility but requiring expertise in model specification.
- **Sensitivity Analyses:** Conducting sensitivity analyses to assess the robustness of results to different model specifications, functional forms, or assumptions is crucial for all methods to enhance the credibility of findings.
- **Reporting Guidelines:** Researchers should transparently report methodological choices, assumptions, sensitivity analyses, and potential limitations to facilitate reproducibility and interpretation of results.

7. Conclusion:**

Difference-in-Differences, Regression Discontinuity, and Slope Difference Models with GLM are valuable tools for causal inference and policy evaluation, each with its unique strengths, assumptions, and considerations. While DID is widely applicable and straightforward, RD offers credible causal inference near discontinuity points, and slope difference models with GLM provide flexibility in modeling outcome distributions and changes in slopes over time. Researchers should carefully select and apply these methods based on the research question, data characteristics, and assumptions, ensuring rigorous analysis and interpretation of causal effects in observational data.