Application of Difference-in-Discontinuity on Household Panel Data: Evaluating the Impact of Cash Transfer Program in Pakistan

Pakistan Institute of Development Economics

By

Muhammad Hayat

(PIDE2019FMHILETS15)

Supervisor

Dr. Ghulam Mustafa

MPHIL ECONOMETRICS

PIDE School of Economics

Pakistan Institute of Development Economics, Islamabad

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Pakistan Institute of Development Economics
P.O. Box 1091, Islamabad, Pakistan

Pakistan Institute of Development Economics

CERTIFICATE

This is to certify that this thesis entitled: **"Application of Difference-in- Discontinuity on Household Panel Data: Evaluating the Impact of Cash Transfer Program in Pakistan"**, submitted by **Mr. Muhammad Hayat** is accepted in its present form by the School of Economics, Pakistan Institute of Development Economics (PIDE), Islamabad as satisfying the requirements for partial fulfillment of the degree in Master of Philosophy in MPhil Econometrics.

Supervisor:	Dr. Ghulam Mustafa	Signature:
External Examiner:	Dr. Faisal Mehmood Mirza	Signature:
Head, PIDE School of Economics:	Dr. Shujaat Farooq	Signature:

Author's Declaration

I am Muhammad Hayat hereby state that my MPhil thesis titled "Application of Difference-in-Discontinuity on Household Panel Data Evaluating the Impact of Cash Transfer Program in Pakistan" is my own work and has not been submitted previously by me for taking any degree from Pakistan Institute of Development Economics or anywhere else in the country/world.

At any time if my statement is found to be incorrect even after my Graduation the university has the right to withdraw my MPhil degree.

Date: 10-Dec-2022

Signature of Student:

Name of Student: Muhammad Hayat

Dedication

This research paper is dedicated to my dear father, who has been nicely my supporter until my research was fully finished, and my beloved mother who has encouraged me attentively with her fullest and truest attention to accomplish my work with truthful self-confidence.

ACKNOWLEDGEMENTS

I am thankful to Almighty Allah, thank you for the strength and power of mind. The completion of this MPhil would not have been possible without the guidance and support of my advisor, Drs. Ghulam Mustafa. This wouldn’t have been possible without the help of my father, brother and friends, so I’d like to thank them, too. Furthermore, I value the love and encouragement of my extended family. Finally, I’d like to express my gratitude to my supervisor for providing me with the studentship that allowed me to complete this thesis.

ABSTRACT

This paper examines the impact evaluation of a program, such programs initiated by the government or non-government authorities or NGOs. The quality of impact evaluation helps to reliable the effectiveness of the programs. In contrast, the impact evaluation also depends on different statistical methodologies to assess variations in outcomes attributed to a proper intervention based on cause and effect analysis. Many econometrics designs or techniques are used as counterfactuals of the impact evaluation. Either these are experimental or quasi-experimental. The average differences between beneficiary and non-beneficiary are the Average Treatment Effect (ATE). Such differences are estimated through multiple techniques widely implemented by the researchers, i.e. Inverse Probability Weighting Regression Adjustment (IPWRA), difference-in-difference (DID), and Regression Discontinuity Design (RDD). Implementing these techniques depends on the nature of the data and the modality of the programs. The main hypothesis and objectives of the study are based on capturing the impact of cash transfer on chronic food security by applying two different models. The study hypothesize that does BISP cash transfer help reduce chronic food insecurity among the benefices, and which technique is more flexible and robust, whether Difference-in-Discontinuity or Inverse Probability Weighting Regression Adjustment (IPWRA). The main objectives of the study are outlined to estimate the impacts of cash transfer on chronic food insecurity among households using Difference-in-Discontinuity and Inverse Probability Weighting Regression Adjustment (IPWRA). The main purpose of the study to compare the estimates of both techniques the Difference-in-Discontinuity and Inverse Probability Weighting Regression Adjustment (IPWRA). The study's findings explore the positive and statically significant impact of the BISP cash transfer on chronic food insecurity. Treatment Effect Model estimates suggest a strong positive and significant impact of BISP cash transfer on food security outcomes. On the other hand, RD estimation also shows a strong positive and statistically significant impact of BISP on food security outcomes. Hence, the overall results show that cash transfer is helping the poor territory to eradicate chronic food insecurity and move them upward to purchase quality food. Somehow the comparisons of the results of the different models (IPWRA) (RDD) and (Diff-in-Dis) show that from the rest of the models, the (IPWRA) is more fixable and robust to estimate the impact evaluation of the program.

Keywords: Impact Evaluation, IPWRA, RDD, DID, Difference-in-Discontinuity, TEM, BISP

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LIST OF ABBREVIATIONS

ATE	Average Treatment Effect
NATT	Average Treatment Effect in Treated
ATET	Average Treatment Effect on Treated
BISP	Benazir Income Support Program
CNIC	Computerized National Identity Card
CPI	Consumer Price Index
DID	Difference-in-Difference
Diff-in-Dis	Difference-in-Discontinuity
FDS	Food Diversity Score
FSI	Food Security Index
GRASP	Growth for Rural Advancement and Sustainable Progress
HH	Household
IPWRA	Inverse Probability Weighted Regression Adjustment
Km	Kilo Meter
LACIP	Livelihood Support and Promotion of Small Community Infrastructure
LATE	Local Average Treatment Effect
LTE	Local Treatment Effect
NGO	Non-Governmental Organization
OPM	Oxford policy management
PPAF	Pakistan Poverty Alleviation Fund
PKR	Pakistani Rupee
POM	Potential Outcome Mean

RDD	Regression Discontinuity Design
SDGs	Sustainable Development Goals

Chapter 01
Introduction

1.1 Background of the study:

Government intervention to target the highly vulnerable and the poor households to enhance their adaptive capacity against economic and non-economic covariate shocks is commonly pursued as a powerful policy instrument. Such intervention includes monetary and non-monetary subsidies, different Labour market-related incentives, and social safety nets. The impact assessment of such programs plays an important role in estimating the programs' effectiveness. Specifically, at the household level, cash transfers are deemed the main form of government intervention to uplift the well-being of the poor segment of society. During the last couple of decades, cash transfers have been highly demanded in developing countries due to their positive and beneficial impacts on curbing poverty and food insecurity among the beneficiaries of the programs (Asfaw, Cattaneo et al. 2017) (Mustafa et al., 2019). The effectiveness of such programs heavily depends on the quality of impact evaluation, which always serves for accountability purpose to highlight how much a program worked and can help to determine the most effective approach (Asian Development Bank, 2006).

The quality of impact evaluation helps to reliable the effectiveness of the programs. In contrast, the impact evaluation also depends on different statistical methodologies to assess variations in outcomes attributed to a proper intervention based on cause and effect analysis. In the counterfactual of impact evaluation, there are many experimental or quasi-experimental designs[1]. The counterfactual analysis can be conducted by identifying the project's potential control group

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[1] https://programs.online.american.edu/online-graduate-certificates/project-monitoring/resources/whatis-impactevaluation#:~:text=Purpose%20of%20Impact%20Evaluation,is%20the%20most%20effective%20approach.

or non-beneficiary. The average differences between beneficiary and non-beneficiary are the Average Treatment Effect (ATE). Such differences are estimated through multiple techniques widely implemented by the researchers, i.e. Inverse Probability Weighting Regression Adjustment (IPWRA), difference-in-difference (DID), and Regression Discontinuity Design (RDD). Implementing these techniques depends on the nature of the data and the modality of the programs (e.g., Mustafa et al., 2019; (Gertler and Giovagnoli 2014); (Wing and Cook 2013); (Lopez-Acevedo and Tinajero-Bravo 2011)).

The impact evaluation of any project requires a specific time duration, such as baseline and follow-up surveys. Evaluation is pursued in follow-up surveys based on the baseline survey. If the project works for a longer period, the follow-ups will be more than one. So, this makes the conducted data a pooled survey as well. In the standard econometric framework, fixed and random effects are the basic models used to evaluate the impact. For instance, (Lopez-Acevedo and Tinajero-Bravo 2011) applied the firm-level fixed effect model to evaluate the impacts of a support program in Mexico to capture firm-level heterogeneity. And the findings of the paper demonstrate that enterprise program has brought about the desired level of outcome variables.

However, to find causal impact through counterfactual analysis, treatment effect models, RDD, and DID are the key techniques to be implemented. Asian Development Bank (2006) highlighted that the choice of a particular technique and methodological framework to evaluate the projects' effectiveness depends on the nature of the data availability and the modality of the interventions. The treatment effect is assigned as a causal effect of a binary variable (0,1) on an outcome variable of policy interest, which could be estimated through social experiment, regression modelling and instrumental variables [2]. (Ahmad, Mustafa et al. 2016) applied the potential outcome treatment effect model to check the impact of adaptation of strategies by farmer households to climate change on food security. (Chernozhukov and Hansen 2006) did work to focus on the estimate of distributional equality, consistency effect, conditional dominance and heterogeneity. For that purpose, they familiarize instrumental quantile regression for heterogeneous treatment effect model, which offers a calculable methodology for inference and estimations. Likewise, regression discontinuity design (RDD) is used as a tool for decision-making to extract the causal effect of different interventions. (Venkataramani, Bor et al. 2016) have explained the strengths and weaknesses while implementing the RDD on evaluating the impacts of clinical medicines and health policy.

Similarly, another study demonstrates that the RDD depends more on assumptions due to its lower statistical power. Its treatment effect estimates are limited around the cut-off in cases of narrow subpopulations (Wing and Cook 2013). DID is also considered a quasi-experimental design in social sciences and econometrics for the difference between pre and post-treatment and controlled and treatment groups in the same scenario of impact evaluation. The DID design is intuitive and flexible if it meets its assumptions and accounts for change due to factors ((Butts 2021); (Galindo-Silva, Somé et al. 2018); (Grembi, Nannicini et al. 2016)).

Somehow, (Callaway and Sant'Anna 2021) has discussed when should not use DID if the treatment amount determines through baseline, different trends in outcome of treatment groups and the comparison of a group being studied are not stable. However, both designs are required

[2] https://economics.mit.edu/files/32#:~:text=Treatment%20effects%20can%20be%20estimated,of%20scientific%20or %20policy%20interest.

to fill the assumptions of impact evaluations. Whereas for RDD, there must be a discontinuity in the probability of exposure at the cut-off. There is no sorting effect or manipulation of forcing variables by the individual, and the exposure groups are transferable around the cut-off. Where the other assumption assumed that in the absence of intervention, the specific outcome probability would be continuous on the cut-off point (Smith, Lévesque et al. 2017). Otherwise, DID has also been based on strong assumptions like paralleled trend assumption that the difference between treatment and control group should be constant over time. DID assumes that intervention or treatment allocation should not be determined by outcome variable. Another assumption is that a stable unit treatment value means that potential outcomes of a unit should not change with assigned treatment to other units. There should be no different varieties for any unit of treatment level that lead to varying possible outcomes (Public health[3]).

1.2 Problem Statement:

As we have discussed before, usually, the nature of the impact evaluation data is household panel data with baseline and follow-up surveys. The main problem is that most researchers apply RDD to estimate the impacts of the intervention on pooled data, while RDD is originally based on cross section data. Which misses the utilization of pooled data, such as the pooled nature helps to understand the time effect and utilization of a large sample size (Mustafa et al., 2019). Nonetheless, in the case of pooled data, we have to go for the household fixed effect or difference-in-difference model. The household fixed effect fails to provide us with the counterfactual analysis due to the structure of the model, although it captures the household specific heterogeneity. So, the alternative is difference-in-difference, widely used to implement the impact

[3] https://www.publichealth.columbia.edu/research/population-health-methods/difference-differenceestimation#:~:text=It%20requires%20that%20in%20the,observations%20over%20many%20time%20points.

evaluation of the intervention or any policy. The implementation of difference-in-difference is problematic when the modality of the program is based on PMT-based targeting, as in the case of the Benazir Income Support Program (BISP) in Pakistan. In such a scenario, the DID's effectiveness is questioned due to cut-off-based targeting. (Grembi, Nannicini et al. 2016) suggested that integrating both RDD and the difference-in difference would cover the limitation of both techniques in the case of household panel data. Difference-in-Discontinuity would allow the removal of time-invariant sorting and compound treatment. Similarly, (Butts 2021) has also suggested the effectiveness of difference-in-discontinuity in evaluating the impacts of public intervention. Moreover, a study by (Monteiro, Cannon et al. 2019) discussed the average local treatment of policy using the difference-in-discontinuity method. Likewise, (Galindo-Silva, Somé et al. 2018) used fuzzy difference-in-discontinuity where multiple treatments were applied to the threshold and identified treatment effects. The effectiveness of the difference-in-discontinuity depends on the assumption of the RDD and difference-in-difference. If the assumptions of both methods are met, then the application of the difference-in-discontinuity would work efficiently and effectively. So, in the case of Pakistan's BISP based on PMT targeting, the application of difference-in-discontinuity could be more effective in evaluating the impacts of cash transfer on different outcomes. It could be essential to unleash the effectiveness of the different assumptions of the RDD and difference-in-difference so that the effective outcomes of the integration of the RDD and difference-indifference could be tested.

Conversely, treatment effect parameters with conditional and unconditional measures could be flexibly estimated using conventional regression techniques. (MaCurdy, Chen et al. 2011) included parameters relying on prevalent propensity score matching and weighting methods approaches. In prior know situations, both the techniques were statistically efficient bound. So the integrated design, difference-in-discontinuity, is assumed to be the good method because it is used by integrating the difference-in-difference and regression discontinuity which needs to be met the assumptions of both said techniques. Alternatively, we have a much more flexible technique known as Inverse Probability Weighting Regression Adjustment (IPWRA). So, utilizing both techniques could change the size and direction of the program. Hence, it will be important to discuss the choice between the difference-in-discontinuity and treatment effect model for quality impact evaluation. (Ahmad and Farooq 2010) applied the potential outcome treatment effect model to check the impact of adaptation of strategies by farmer households to climate change on food security. (Chernozhukov and Hansen 2006) did work to focus on the estimate of distributional equality, consistency effect, conditional dominance and heterogeneity. For that purpose, they familiarize instrumental quantile regression for heterogeneous treatment effect model, which offers a calculable methodology for inference and estimations.

1.3 Hypotheses/research questions:

The study would test the following key hypothesis.

1. Does BISP cash transfer help to reduce chronic food insecurity among the benefices?
2. Which technique is more flexible and robust, whether Difference-in-Discontinuity or

   Treatment Effect Model.

1.4 Objectives:

Overall, the underlying study focuses on implementing and comparing the difference-in-discontinuity and Treatment effect model to evaluate the BISP's impacts on chronic food security. Nonetheless, the specific objectives of our study are outlined as follows.

- To estimate the impacts of cash, transfer on chronic food insecurity among the households by using Difference-in-Discontinuity
- To estimate the impacts of cash, transfer on chronic food insecurity among households by using the Treatment Effect Model
- To compare the estimates of both the Difference-in-Discontinuity and Treatment Effect Model.
- To analyze the key polices and different assistance programs to reduce chronic food insecurity and poverty.

1.5 An Overview of Benazir Income Support Program:

The social protection programs provide contextual policies and formulated mechanisms to evaluate the poor, vulnerable household's protection against covariate and idiosyncratic shocks. Against these shocks, the Government of Pakistan provides social safety nets that follow the ad hock policies recommended against problem occurrence. In 2008 federal Government initiated a program named (BISP) the Benazir Income support program for food prices shock assistance. The BISP focuses on the primary objective of restraining the inverse impact of fuel and food consumption with financial crises.

The financial assistance program BISP also aims to empower women, reduce poverty, and build the capacity of vulnerable households to poverty. The program was launched through the parliament act (Act No XVII of 2010) and is an autonomous body of federal (GOVT of Pakistan). By the end of 2017, cash transfer provision reached over 5.7 households receiving 5000 PKR quarterly. Somehow BISP underlying some key objectives and goals, which are in the form of financial assistance to poor households and enhancing the financial capacity of dependent family members. The program also aimed a key objective to support low-income groups to eradicate poverty; in other words, it promotes equal wealth distribution among people.

On the other side, it formulates some comprehensive policies and the implementation of targeted programs to enhance the quality of the lives of underprivileged and vulnerable households. BISP provide financial support to women in the form of financial support [4].

The BISPs beneficiaries number increased to 5.17 million in 2016, which was 1.7 million in 2008/2009. The BISPs amount disbursement also increases from Rs. 16 billion to Rs. 69.65 billion in the years 2008/2009 to 2016, respectively. The total amount of the disbarment reached Rs. 412 billion in 2008. Alternatively, BISP uses Oxford policy management as a third-party research organization that estimates the program's effectiveness as a tool for poverty erosion. OPM just completed some rounds to check the impact of the program, which will be helpful for stakeholders to determine the efficiency of the program in delivering its aims. However, it is observed that BISP significantly affects women's mobility in a community role and increases monthly food consumption per adult to 69 PKR [5].

[4] https://bisp.gov.pk/overview/
[5] https://bisp.gov.pk/SiteImage/Misc/files/BISP-Policy-Brief.pdf

The evaluation is based on the mechanism of household surveys from four different provinces of Pakistan. Somehow BISP has some secondary impacts according to the livelihood and education of the households. The specific findings regarding livelihood designate the occurrence of the overall reduction in dependency on causal labor. Education findings, on the other hand, revealed no evidence of enhancement of children's school attendance due to BISP cash transfer.

To enhance children's enrolment in school, especially girl child, BISP played a small but important role in enabling beneficiaries to graduate out of poverty. At this point, BISP provides bonfires to 100,000 plus children in Punjab province as a Waseela Taleem program [[6]].

1.6 Significance of the Study:

The underlying study will carry two types of significance: one is a contribution to literature, and the second will be considered an effective tool for policy formulation. Literature-wise, we will collect some studies that belong to different methodologies used for impact evaluation of the programs. A study by (Meng 2013) evaluated the impact of poverty alleviation of China on rural income growth at the country level. The research study used a regression discontinuity design to estimate the causal impact of the program using panel data. Another study by (Wing and Cook 2013) used Difference in discontinuity design to practice public health policy. The paper tries to build comparison groups to check robustness and sensitivity analysis for assumption validation. Also explained is that DID is not suitable for the randomized experiment but is the best way to estimate causal relationships. Somehow (Iqbal, Farooq et al. 2021) used regression discontinuity design to measure BISP cash transfer causal effect on women empowerment using the RDD and Difference-in-difference approach to assess the impact on treatment and control group. Outcome

[6] https://bisp.gov.pk/NewsDetail/NmRkM2IzOWEtNmYxNS00NzYyLTk0NDUtODJiNzI2ZjMwNDcz

variables were in the form of, i.e. gender norms, autonomy mobility to different places and socio-economic and political empowerment. But in our study, we try to present a best-integrated design; this study will conduct the same scenario in integrating Difference-in-Discontinuity design.

However, a study by (Galindo-Silva, Somé et al. 2018) used a fuzzy discontinuity design and applied multiple treatments at the threshold under the specific assumption that changes in probability were equal across the treatment at the cutoff. The Difference-in-discontinuity identified to estimate the effect of interest treatment relies on milder proposed assumptions. An article by (learning platform) has used the Diff-in-Dis model to highlight the effects of covid-19 on environment policies to shape air quality. A paper by (Grembi, Nannicini et al. 2016) followed the same methodology and discussed why they could not adopt Regression discontinuity because of another policy that changes sharply at the threshold. Somehow also explained that we cannot only Difference-in-difference design because in public policy the small and large municipalities were on differential trends. Somehow our study will be based on model integration difference and discontinuity; the base paper used the methodology to show the data's causal impact. But our study will focus on methodology and use data as a case for the integration of two models. A solid analysis should be built via integration rather than applying these designs individually or partly to check impact evaluation.

Somehow a study by (Torres-Reyna 2007) essay on political economy and public finance presented the same difference-in-discontinuity design. That evaluates the effect of relaxing fiscal rules on policy output, combined before and after variation and discontinues policy. However, on the policy formulation side study will focus on building or providing the best model (design) that evaluates governmental projects with robust estimation. Rather than being involved in DID and RD individually, study will provide a solution to compress these designs into one built model or design. That might be helpful in upcoming impact evaluation projects from the government, considering beneficial or non-beneficial scenarios.

Alternatively, we have a much more flexible technique known as Inverse Probability Weighting Regression Adjustment (IPWRA). Conversely, treatment effect parameters with conditional and unconditional measures could be flexibly estimated using conventional regression techniques. (MaCurdy, Chen et al. 2011) included parameters relying on prevalent propensity score matching and weighting methods approaches. In prior know situations, both the techniques were statistically efficient bound. (Spieker, Delaney et al. 2015) researched why traditional approaches are unsuitable when medication use relies on biomarker values. For that purpose, they demonstrate how Heckman’s treatment effect model can provide lodging with this feature, which gives rise to cross-sectional data. Heckman's model was more precise than different methods. (Andresen 2018) explained the marginal treatment effect permit going thorough average treatment effect to estimate the distribution of effects. For that, they introduced a Stata package (mtefe) which improves calculation and flexibility in treatment effect parameters. So, the utilization of both techniques (Difference-in-Discontinuity, Inverse Probability Weighting Regression Adjustment (IPWRA)) could change the size and direction of the program. Hence, it will be important to discuss the choice between the difference-in-discontinuity and treatment effect model for quality impact evaluation.

Chapter 02
Literature Review

2.1 Impact Evaluation Program:

An introduction to impact evaluation an article by (Ravallion 2001) provided the concept, method, and intuitive concrete context explanations, which learnt the ex and post-impact evaluation method with related strengths and weaknesses. A relevant study conducted by Walle (2009) on rural road projects discussed the assigned project to a specific geographic area no other, where intervention is assigned to households, firms etc. In the same way, a research paper by (Iqbal, Farooq et al. 2021) evaluated the impact of unconditional cash transfer (BISP) estimated by two follow-up years (2011&16) as a baseline survey and follow-up round. In our study, the relevant case of BISP cash transfer payment with the follow-up years is taken for estimation too. Recent studies will conduct the same impact evaluation process but focus on choosing effective design that provides a simple but broad evaluation.

2.2 Panel Data Evaluation:

The above paragraphs explained the impact evaluation of unconditional cash transfer programs provided to poor households. Panel data is a data set in which behavior entities are observed across time, also known as longitudinal or cross-sectional time-series data. A research study by (Rogers 2009) explained assigning the appropriate design and method choosing for impact evaluation that provides information about the impact of the intervention. Somehow a study by

(Chernozhukov and Hansen 2006) used panel data to estimate the impact of social policy. By

(Nguyen 2012), the panel data are always collected after the beginning of an intervention.

However, panel data is compared to cross-sectional and time-series widely portrayed observational designs because both provide control for observable and unobservable that correlate without also coming with a program exposure (Gertler and Giovagnoli 2014). The following literature of our study will build some paper reviews to find the best model for panel data estimations. The panel data used a different design that evaluated the impact of programs. A recent study aimed to find other literature or methodologies that used the panel data for impact evaluation.

2.1.1 Review of Fixed Effect Model:

Along with the panel data, a study by (Gertler and Giovagnoli 2014) was presented to evaluate the public program; for experimental design, the paper used the most popular linear and fixed effect estimator evaluation design. To sort out gander differential to allocate resources, (Subramaniam 1996), in his paper, presented panel data fixed effect results and discussed that no longer gander differential occurred in resources allocations. The fixed-effect model with multiple observations estimates the effect of variables changing across observations (Greene 2009). According to (Torres-Reyna 2007), the fixed effect is used whenever we are only interested in analyzing the impact, which varies over time in variables and exploring the relationship of predictor and outcome variables. Based on the assumption that the fixed effect removes time invariant characteristics, the characteristics were unique and not correlated with other individuals' characteristics.

2.1.2 Flexibility of Treatment Effect Model:

The treatment effect is assigned as a causal effect of a binary variable (0,1) on an outcome variable of policy interest, which could be estimated through social experiment, regression modelling and instrumental variables. (Ahmed, Al-Amin et al. 2016) applied the potential outcome treatment effect model to check the impact of adaptation of strategies by farmer households to climate change on food security. (Chernozhukov and Hansen 2006) did work to focus on the estimate of distributional equality, consistency effect, conditional dominance and heterogeneity. For that purpose, they familiarize instrumental quantile regression for heterogeneous treatment effect model, which offers a calculable methodology for inference and estimations.

The Inverse Probability Weighting Regression Adjustment (IPWRA) is a much more flexible technique compared to other evaluation methods. Conversely, treatment effect parameters with conditional and unconditional measures could be flexibly estimated using conventional regression techniques. (MaCurdy, Chen et al. 2011) included parameters relying on prevalent propensity score matching and weighting methods approaches. In prior know situations, both the techniques were statistically efficient bound. (Spieker, Delaney et al. 2015) researched why traditional approaches are unsuitable when medication use relies on biomarker values. For that purpose, they demonstrate how Heckman's treatment effect model can provide lodging with this feature, which gives rise to cross-sectional data. Heckman's model was more precise compared to different methods. (Andresen 2018) explained the marginal treatment effect permit going thorough average treatment effect to estimate the distribution of effects. For that, they introduced a Stata package (mtefe) which improves calculation and flexibility in treatment effect parameters.

2.1.3 Critical review of Regression Discontinuity Design:

The regression discontinuity design is another quasi-experimental design that evaluates the causal effect of the intervention (Imbens and Kalyanaraman 2012). Regression discontinuity design (RDD) is used to make decisions to extract the causal effect of different interventions. (Venkataramani, Bor et al. 2016) have explained the strengths and weaknesses while implementing the RDD on evaluating the impacts of clinical medicines and health policy. Similarly, another study demonstrates that the RDD depends more on assumptions due to its lower statistical power.

Its treatment effect estimates are limited around the cut-off in cases of narrow subpopulations (Wing and Cook 2013). A paper used election data to find personal incumbency advantage, where estimation discussed no incumbency advantage (Hyytinen, Meriläinen et al. 2018). The conventional polynomial RDD estimates are significant, which affects the results moderately, and statistically, the RDD generates robust inference with Bias corrected estimation.

According to world bank data (Dime Wiki), RDD has a cutoff point for determining eligible participants. The Paper covered introducing when to use fuzzy vs sharp RDD design was used to interpret treatment effect. In the paper, the necessary assumption (eligibility index around the cutoff should be continuous, close to the cutoff individual (observed and unobserved) should be same in average and condition (clearly defined cutoff and continuous eligibility index) for RD design. Somehow on the bases of advantages and limitations, a paper by (Hahn, Todd et al. 2001) discussed that RDD raised many questions about variables, which were further included in the model. Whereas in limitation research paper discussed the RD design only identifier of local effect at the point, probability assignment to treatment changes discontinuously. According to Wikipedia the estimated effect is unbiased if the relationship among treatment and control group correctly modeled, the limitation is the non-linear relationships which are mistaken in discontinuity. Another limitation is contamination by other treatments, means that the measured discontinuity in outcome variable may attributed to other treatment. Somehow a paper by (Lee et al, 2010) detailed that how RDD valid and invalid given economic incentives. Authors literately explained that there is no comprehensive summary what understood about RD, when it succeeds and fail, and with are the flaws and strengths of the design. The Authors discussed the manipulation or sorting is the general issue. They also explained that the graphical representation of RD is helpful but the visual representation should not be informative or helpful to finding the effect or no effect.

2.1.4 Strength and Weakness of Difference-in-Difference Design:

The DID design by (Stata17), a non-experimental design, estimated the treatment effect and compared the difference between the mean of the outcome of treatment and the control group across time. DID is also considered a quasi-experimental design broadly used in social sciences and econometrics for the difference between pre and post-treatment and controlled treatment groups. The DID design is intuitive and flexible if it meets its assumptions and accounts for change due to factors (Butts, 2021; Galindo-Silva et al. 2018; Grembi et al., 2016). Somehow, (Callaway and Sant'Anna 2021) has discussed when should not use DID if the treatment amount determines through baseline, different trends in the outcome of treatment groups and the comparison of the group being studied are not stable. By (Angrist and Krueger 1999), DID is a panel data method applied when certain groups are to expose the interest of a variable. Implementation of DID by a study (Imbens and Lemieux 2008) took two differences between groups, the mean of the outcomes and the causal impact between groups of causal variables.

A research article of the world bank (Dime Wiki) explained that DID facilitates causal inferences at the non-possibility of randomization. DID legitimacy depend on the assumption of similar trends between the treatment and control groups; no time-varying differences exist. Somehow some articles and papers presented the strength and weaknesses of DID model. An article (Statistics how to) presented that DID is a fairly stretchy and spontaneous method, based on the assumption that DID show causal effect through observational data. DID focuses on variation or change rather than the absolute level. Somehow the article presented some limitations of the model; one of those limitations was to use DID always needs non-intervention groups and baseline data (Statistics how-to). The article also suggested that we also shouldn't use it if the amount of treatment is determined by baseline, different trends in comparison group outcomes and their composition are not stable.

A paper (Michael Lechner, 2011) explained causal effect estimation through DID a brief overview of the literature on the difference-indifference (DiD) estimation strategy and discusses major issues using a treatment effects perspective. The same paper also explained some issues regarding DD, with availability of finite number of groups or periods, time specific randomness then no consistent estimator can exist, due to which within group averaging can't eliminate such variability. On the same scenario a paper by (Bertrand et al., 2004) how should trust on DD estimates, in detailed paper conducted different study which specified issues regarding DD. In which majority of papers highlighted grouped error terms when unit of observation is more detailed than the level of variation. Some of them address serial correlation issue, while some of by data aggregating or clustering standard error, some of those report standard error that understate the standard deviation of DD estimator.

2.1.5 Integration of Difference in Difference and Regression Discontinuity Design:

Kyle Butts, in his paper geographic difference-in-discontinuities, critiqued to use of regression discontinuity due to administrative cutoff. It is difficult to identify when multiple treatments can change at the cutoff, and individuals can easily sort either side of the cutoff (Butts 2021). The Diff-in-Dis design was applied to check the impact of fiscal rules on reducing incentives to accumulate debt where a post-treatment identifies the previous two discontinuities and the other one caused by treatment of interest (Grembi, Nannicini et al. 2016). Kyle Butts, our study also formulates efficiency to estimating this specific model to report the problem of categorization around the cutoff. However, a study by (Galindo-Silva, Somé et al. 2018) used a fuzzy discontinuity design and applied multiple treatments at a threshold under specific assumptions. That changes in probability was equal across the treatment at the cutoff, and Difference-in-discontinuity identified to estimate the effect of interest treatment relies on milder assumptions. The Diff-in-Dis design was also used to estimate the impact of covid-19 on environmental policies that shaped air quality.

2.4 Description:

Above all literature buildup, the study presents how all these designs are strong or limited to sort out the problem of causality or to evaluate the program's impact on individuals. Our study builds econometrics literature to present a best-fitted model without bias or limitation. Our study integrates regression discontinuity and difference-in-difference designs to build an integrated strong design difference-in-discontinuity. Like (Grembi, Nannicini et al. 2016), our study will also formalize the same integration for impact evaluation of the unconditional cash transfer program of BISP and to address the problem of categorization around the cutoff. Alternatively, we have a much more flexible technique known as Inverse Probability Weighting Regression Adjustment (IPWRA).

Conversely, treatment effect parameters with conditional and unconditional measures could be flexibly estimated using conventional regression techniques. So, the utilization of both techniques (Difference-in-Discontinuity, Inverse Probability Weighting Regression Adjustment (IPWRA)) could change the size and direction of the program. Hence, it will be important to discuss the choice between the difference-in-discontinuity and treatment effect model for quality impact evaluation.

Chapter 03

Theoretical Framework:

Principally, BISP cash transfer has two main objectives: short-term objective, which support poorest people from the opposed shock of food prices. The other long-term is the amount which allows the receiver to plan necessary investment in basic needs with education and resources. That potential investment further helps individuals recover physical and human capital, enhancing their breathing capacity out of severe poverty (Government of Pakistan, 2014). Somehow many studies on cash transfer programs highlight the significant positive impact of the different cash transfer programs (i.e. (Fiszbein and Schady 2009); (Villa and Niño-Zarazúa 2019); (Peterman, Kumar et al. 2020)).

Somehow BISP theory accepts that in the short run, cash transfer has two types of effects on household spending: expenditures on food and non-food. The intermediate impact of BISP cash transfer is probable to enhance the daily food calorie intake and its diversification. That further enhances the capacity of nutrition in beneficiaries' households in the long term (figure-3.1). On the other hand, the noon food expenses include health and educational spending, where the attainment of such expenditure in the intermediate term may lead beneficiaries in the long run towards healthy life and progression of schooling.

The following process of the BISP cash transfer program, along with the expenditure of households, can be highlighted in the consumer behavior framework through the Stone Gary function of utility same as used by (Kamakura and Mazzon 2015). They have projected that budget constraints could influence the distribution of BISP cash transfers. Consequently, the disbursement of cash transfers enhances the income of households and should directly influence their food and non-food expenditure allocation. The BISP cash transfer was specifically inaugurated for the extremely poor citizen, which enhances the household's capacity to spend more on food and non-food commodities.

That’s why (Kamakura and Mazzon 2015) introduced a budgetary allocation model to sort out the impact of household expenses through a cash transfer program. That model helps to eradicate the different features of consumption designs to compare the beneficiaries and non-beneficiaries of the program.

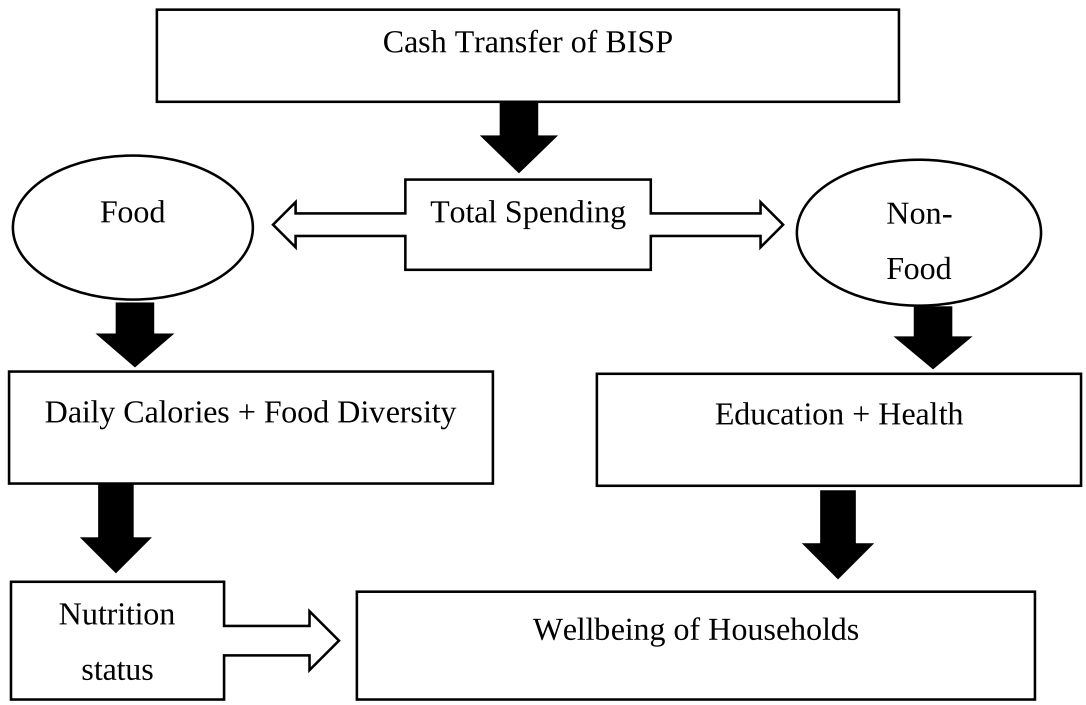

Figure 3.1: Conceptual framework of Cash Transfer of BISP and Expenditure of Households.

However, such designs possess how these beneficiaries formulate their expense on food items and nutritious status due to cash transfer. On the other hand, it also helps to demonstrate how these beneficiaries’ households allocate this cash to different food items. At least the model also permits rectifying the comparison between beneficiaries and non-beneficiaries' behavior due to cash transfers.

To consider the studies of Du and Kamakura (2018) and Kamakura and Mazzon (2015), the underlying study converts their already used model to expenditure on food to highlight the connection between food outcomes and cash transfer of BISP among different beneficiaries. For that so, it is supposed that beneficiaries' households exhaust the direct function of utility G(ci) over the set of j non-negative amounts ci = ($c1i$, $c2i$ …….. cji) it includes all the categories of food subjected to constrain of budget $pi\ ci$ = mi, in which pi represents the prices of food items; on the other hand, mi represents total income.

The underlying study uses Stone Gary's utility function that Kamakura and Mazzon (2015) identified to evaluate the impact of BISP cash transfer.

$G(ci) = \sum_{j=i}^{j} \alpha ji\ \text{In}(cij - \beta j)$ (3.1)

In equation 3.1, where aji > 0 indicates definite taste parameters of households that identify priority among different categories of food items with ($cji - \beta j$) > 0. Where the allocation of cash on those types of items that yield high marginal utility per unit (rupee) by household is, Same as $\frac{\left(\frac{\partial ci}{\partial cji}\right)=aji}{(cji-\beta j)}$, prior given their level of consumption ci with budget limit approaches to $\sum_{j=i}^{j} cij = mi$.

As considered in the study of Kamakura & Mazzon (2015), the underlying study specified the same model for the value indulged with every consumption category by overlooking prices. Where the same model highlight expenditure preferences of households that are also sustained by the change theory of BISP. In the underlying study, we assume that poor households spend more on food items to meet the dietary requisites. These requisites enhance the capacity of lower households to food security level via daily calorie intake and food diversity to expand food baskets.

Chapter 04
Data and Variables

4.1 Data source:

Our study employs household-specific variables where the variables are constructed based on BISP (four waves) survey data, which employ household and community-based survey data. The Oxford policy management (OPM) services hired by BISP and rigorous impact assessment reports. Both households and community surveys follow up on (the 2011, 2013, 2014 and 2016) baseline years. The BISP socio-economic characteristics survey carries the same available households in baseline, but the survey also has some additional households for the 2016 follow up year. In the 2011 survey baseline, the four provinces from which 90 districts are led in 488 (neighbor hoods and villages) clusters; that survey was completed in July 2011. The prior collection with a sample of 8675 households of the program was randomly drawn from specified clusters. From 2013&2014, follow-up year surveys with the same households for comparison purposes were classified into a beneficiary and non-beneficiary household individuals. However, some households are excluded from the follow-up survey because they do not have the CNIC number; somehow, a few households with a 10 per cent attrition rate are unavailable in respective follow-ups.

The following table shows final panel information with 8221 and 7487 follow-up years (2013&2014); a total of 7778 households in the 2014 survey has covered. These households in 2014 remain appropriate in the 2016 follow-up with 11395 surveyed households, but those do not have CNIC and PMT scores. Of the total households surveyed, 3713 were from the 2011 baseline; other 7682 were additional in the 2016 survey baseline (Government of Pakistan).

Table 4.1: BISP Beneficiaries and Non-Beneficiaries status with information from Follow-up survey

	Baseline Survey (2011)		1-Follow-up Survey (2013)		2-Follow-up Survey (2014)		3-Follow-up Survey (2016)	
	Beneficiary	Control	Beneficiary	Control	Beneficiary	Control	Beneficiary	Control
Punjab	819	2198	802	2215	729	2102	2397	1982
Sindh	1346	981	1303	1024	1155	1103	2235	1355
KPK	833	1075	820	1088	823	1009	1635	1096
Baluchistan	251	718	251	718	163	694	367	328
Pakistan	4972	3249	5045	3176	2870	4908	6634	4761
Total	8221		8221		7778		11395	
Panel HH	------------------------		8221		7487		3713	

The survey baseline with the final sample size carries 8221 households with 4972 program beneficiaries and 3249 non-beneficiaries. For further detail, the 2013 follow-up year possesses the least or exact final sample size; somehow, the 2014 baseline comprises 4908 control and 2870 beneficiaries' households.

4.1.2 Poverty Score:

The underlying study will use the same poverty score (16.17) (Iqbal, Farooq et al. 2021) because the study's main objectives rely on testing the effectiveness of the assumptions of both different designs. So the study will use the same poverty score (16.17) where around 7.7 million households have been identified as most eligible because their estimated poverty score is less than the estimated poverty score (16.17). All ever-married women from households with CNIC are eligible for the program but must register their selves near the local office of BISP. Somehow cut-off up to a score of 20 is an exception for eligibility, but some conditions must full fill for this exception (Ambler and De Brauw 2019).

4.2 Variables Construction:

The construction of variables part of this study will discuss all household variables in detail that engage all the objectives being estimated. Following are the description of those variables.

4.2.1 Variable Description:

As we know, the treatment is a binary variable with the value of 1 when the household's value is less than the poverty score of 16.17, where zero value indicates the non-beneficiary status of the household. The food security outcome is measured via three to four methods. These comprise calorie intake, food diversity score, weekly food availability and food security index which generate from the first three indicators normalized to make (FSI) unit free, normalizing through the equal weighting method.

Table 4.2: Detail of treatment, control and outcome variables

Name of Variable	Variables Description	Units
Treatment	If they take BISP cash, it takes values 1; otherwise, 0	0,1 binary
	Outcomes	
Food Diversity	Food diversity scores were taken for 13 groups of food; with higher the score value, the more diversification.	In numbering
Daily calories intake	Consumption of kilocalories of food commodities that multiply with particular food consumed items to divide by each adult score.	In Days
	Variables that are Control	
Household size	Number of total members of the household	Scale
Household Head sex	Gander identity of a household member	Numbers
Household Head age	Age of household at survey conduction time	Numbers
Matriculation Edu	Education of household who did only matric	Binary
Intermediate Edu	Education of household who did only intermediate	Binary
Above inter Edu	Education of household other than matric and intermediate	Binary
Female ratio	The total number of females in the household is compared to male	Ratio
Distance bus stop km	Distance from house to the bus stop in km	Numbers
Distance market km	Distance from house to market in km	Numbers
D-region1	From which region do they belong	Binary
Period	Survey baseline period (2011,2013,2014&2016)	Binary

The following table briefly discusses different variables such as treatment, outcome and controls utilized by this specific study.

4.2.2 Treatment variables:

Treatment variables are the core variable that sorts out the households with the beneficiary and non-beneficiary status. The household classification is already specified based on a 16.17 cut-off poverty score. Households below the cut-off considered are a beneficiary of BISP or treatment group. Some households whose poverty scores range from 16.17 to 20 also considered is beneficiaries due to eligibility criteria exceptions. Whose take BISP beneficiary considered is binary treatment variable with value 1, zero is considered non-beneficiary.

4.2.3 Outcome variables:

The outcome variable of the underlying study is food security; the following are the further detail of this outcome variable.

4.2.3.1 Food Security:

Food security is the other outcome variable of this underlying study. In contrast, its construction is based on three indicators: calorie intake, food diversity score and availability of food items on average. Where stable availability and food access are the two main dimensions of food security ((Ahmad and Farooq 2010); (Ahmad, Mustafa et al. 2016)), we initially combine all indicators by assigning equal weights to average them. The Index ranges from 0 to 1. However, with a high FSI value, food security will be high among households.

Daily Calorie Intakes:

Daily calorie intake is an important indicator of food security; for computation, the food consumption items have converted into kilograms. For further computation, the food product is multiplied by the kilo calorie amount, giving us the daily kilo calories intakes of households. To transform this measure into adult equitant, the Government of Pakistan (2014) estimated it to divide daily calories intakes by per adult household equivalent size. Where value 1 is assigned to those above 15 years old, whereas 0.8 is assigned for those below 15 years old (Asfaw, Cattaneo et al. 2017).

Food Diversity Score:

The food diversity score is another important indicator of food security, commonly computed by counting the thirteen groups of foods given by the BISP survey. The FDS value range from 0 to 13, where much literature employed food diversity as an indicator of food security ((Hidrobo, Hoddinott et al. 2018); (Tiwari, Daidone et al. 2016); Government of Pakistan, 2016).

Food Availability on Weekly Bases:

Food availability is one other indicator of food security, measured by the availability of particular food groups in the number of days during a week. Which explore continuous accessibility and availability of food items to households. This indicator explained the stability element of food security (Ahmed, Al-Amin et al. 2016). Where the average value of this measured indicator rage from 0 to 7 days per household.

4.2.4 Control variables:

The underlying study uses the control variable from the BISP's survey of households, which includes the age of head, gender of head education of HH head, dependency ratio, unemployed ratio, and female ratio. Where some more community-based variables were also included when pooling the sample.

Chapter 05
Methodological Framework

5.1 Econometric Framework:

The underlying study aims to evaluate the effectiveness of difference in discontinuity, which is the integration of both RD and DID and set a comparative analysis between the difference-in discontinuity and Inverse Probability Weighting Regression Adjustment (IPWRA). The impact of BISP unconditional cash transfer on food security is the case for applying this integrated design difference-in-discontinuity. Somehow study also have a determined objective to use the same data for the Inverse Probability Weighting Regression Adjustment (IPWRA), further both the results of these two different models are used for comparison purpose. Where the underlying study used micro panel data of households with follow-up years (2011-2016). A study by (Ahmed, Al-Amin et al. 2016) applied the potential outcome treatment effect model to check the impact of adaptation of strategies by farmer households to climate change on food security, which is considered a flexible model for impact evaluations. The Integrated design of Regression Discontinuity (RD) and Difference-in-difference will provide a quick solution which a more efficient and robust design for impact evaluation. However, the methodology of Diff-in-Dis is backed by strong literature (Grembi, Nannicini et al. 2016), (Hong 2017) etc. The underlying study used BISP follow-up survey data to check the impact of the BISP program on chronic food insecurity.

5.2 Difference-in-discontinuity Design:

According to relevant research papers that used the same integrated design. We will construct our methodology with the same process as other relevant papers used. In our study Yit represent dependent Outcome variables i for gender norms, women's mobility, and socioeconomic and political empowerment respectively at the time t. Where Yit=1 is the potential outcome in the case of treatment $Dit = 1$, otherwise for the potential outcome of $Yit = 0$ is the case for no treatment $Dit = 0$. The treatment year T_0 that is if $t \geq T_0$ only BISP programs below a certain population cutoff Pc are treated. The running variable Pi is a set at the PMT score that is time-variant. The treatment assignment will in our study is the following.

$$\mathrm{Dit} = \{10 \text{ if } \mathrm{Pi} \leq \mathrm{Pc}, \mathrm{t} \geq \mathrm{TO}\} \quad \text{otherwise}$$

To define the average treatment effect on female households at the threshold Pc represent by the neighborhood Average treatment effect of the treated (NATT). Which shows the effects of interventions or treatments on those who received in a target sub-population via the presence of treatment heterogeneity or the projection of potential outcomes. All the estimations will take place under the Difference-in-discontinuity assumptions.

Our outcome estimating equation will be the same as Iqbal et al, (2021) used in their conducted study.

$$\mathrm{Yit} = \beta 0 + \beta 1 \text{ time} + \beta 2 \text{ bisp\_treat} + \beta 3 (\text{time} * \text{bisp\_treat}) + \mathrm{FE} + \varepsilon \ (1)$$

Here the Yit shows the outcome variables of food security explained above are food diversity and daily kilo calories intake, β0 is the constant term, bisp_treat is a dummy variable, '0' is the indicator for the non-beneficiary group and '1' indicates the beneficiary group. Time is also a dummy variable with 0 if the time is 2011 and 1 if the time is 2016; time*bisp_treat is the interaction term, the product of time and bisp_treat; FE is each household's fixed effect and ε is the error term. Here β3 is the coefficient of the model. The negative value of β3 depicts the negative impact of the BISP cash assistance on food security indicators whereas the positive value of β3 indicates the positive impact of BISP cash assistance over time.

To build the Difference-in-discontinuity model for estimation we will take the following equation which was used by Germbi (2012) in his paper.

$$Yit = \delta 0 + \delta 1P * i + Ji\,(\gamma 0 + \gamma 1P * i) + Tt\,[\alpha 0 + \alpha 1P * i + Ji\,(\beta 0 + \beta 1P * i)] + \xi it \quad (2)$$

Where Ji is a dummy for households below PMT score, Tt is an indicator for the post-treatment period, and $P * i = Pi - Pc$ the normalized population size. Standard errors are clustered at the household level. The coefficient β0 is the diff-in-disc estimator and identifies the treatment effect of BISP unconditional transfer, as the treatment is$Dit = Ji.Tt$. This study will present the robustness of results to multiple bandwidths h. where Iqbal et al, have used the fixed bandwidth +/-.

$$\check{T}DD = (Y^{-} - Y^{+}) - (\bar{Y}^{-} - \bar{Y}^{+}) \quad (3)$$

We call $\check{T}DD$ is a Difference-in-Discontinuity estimator because it is backed on the intuition of combining DI D and RDD.

5.2.1 Difference-in-Discontinuity Design Assumptions:

The underlying study is aware of that; other empirical studies have already used the Difference in-Discontinuity design. But here study provides clear identification of assumptions to highlight this approach with diagnostic tools (Grembi et al, 2016).

1) All potential outcomes $E\ [Yit\ (w, r)\ |Pit = p, t \geq t0]$ and $E\ [Yit\ (w, r)\ |Pit = p, t < t0]$, with w = 0,1 and r = 0,1 are continuous in p at Pc.

2) The effect of the confounding policy Wit at Pc, in the case of no treatment, Rit = 0 is constant over time: $Y\ (1,0) - Y\ (0,0) = \bar{Y}\ (1,0) - \bar{Y}\ (0,0)$.

3) The effect of the treatment Rit at Pc does not depend on confounding policy

$Wit: Y\ (1{,}1) - Y\ (1{,}0) = Y\ (0{,}1) - Y\ (0{,}0) \equiv Y\ (1) - Y\ (0)$

5.2.2 Motivation to apply difference-in-discontinuity technique:

The regression discontinuity has been broadly used design for impact evaluation of the program, due to non-parametric test estimation is controlled to simple requirements. Suppose cross-sectional data with one running variable. Somehow, many studies used it for parametric polynomial or with arbitrary bandwidth [Dell (2010) applied for two dimensional RD and Grembi et al., (2016) applied it for Diff in Dis]. To solve this, the aim is to build a program such as (rdrobust) which possesses flexible term of specifications. To follow the rules, the (ddrd) platform is constructed upon (rdrobust package), which comprises the following solutions (diff-in-discontinuity and diff-in-kinks, multiple running variables, control variables, Analytic weights, and heterogeneous effect over linear interaction). These choices are to be taken to use the diesel package for optimal bandwidth computation.

5.2.3 Representation of difference-in-discontinuity and Kink:

Suppose $\mu t(x) = E[Y\ |X = x, t]$ and $\mu t^{(v)}\ (x) = \frac{\partial^{v} E[Y\ |X{=}x{,}t]}{(\partial x)^{\ v}}$

So the conventional Regression Discontinuity and Regression Kinks estimator be written as follows;

$$\tau v, t = \lim_{x \to 0+} \mu t^{(v)}\ (x) - \lim_{x \to 0-} \mu t^{(v)}\ (x) = \mu t +^{(v)} - \mu t -^{(v)} \qquad (4)$$

The difference-in-discontinuity and Difference-in-Kinks estimator be written as:

$$\Delta\tau v = \mu 1 + (v) - \mu 1 - (v) - [\mu 0 + (v) - \mu 0 - (v)] \qquad (5)$$

Whereas, optimal bandwidth for h* can be estimated as;

$$h * MSE = \left[\frac{Var(^{rv})}{Bias(^{rv})\text{^}2}\right]^{\frac{1}{5}} n - 1/5 \qquad (6)$$

These estimators are taken from [(Imbens and Kalyanaraman 2012) and (Calonico, Cattaneo et al. 2014)]. Where for difference-in-discontinuity and Difference-in-Kinks they used τv by Δˆτv instated of ($\hat{}\tau v$) and $Bias(\hat{}\tau v)$ 2. That's what the package (ddbswel) does for these estimations, on the other hands (ddrd) package estimates the robust, bias-corrected confidence intervals for Δˆτv, as projected by [(Calonico, Cattaneo et al. 2014)].

5.2.4 Regression Discontinuity:

The underlying study centers to implement the assumptions of Regression Discontinuity, which is a quasi-experimental design to estimate the impact evaluation. However, the BISP eligibility criteria are based on the poverty score (the cutoff point). To evaluate the effectiveness of the program, the co-comparison of treatment and control groups not be more effective because of the confounding effects of the program due to other systematic differences in beneficiaries and non-beneficiaries. Where the program is suitable for applying Regression Discontinuity that allows co-comparison in marginally eligible and in-eligible households 16.17 is the PMT score.

The Regression Discontinuity Design evaluates local average treatment effect (ATE) due to its local nature, lid households nearer to both sides of the eligibility criteria (Ambler, Brauw, 2019).

$$Yi = \beta_0 + \lambda Ti + \beta_1(X - C) + \beta_2 T * (X - C) + \mu_i \qquad (7)$$

In the following equation, c refers to the cut-off which represents the poverty score for BISP (16.17), X represents a continuous variable of poverty score, where T is a binary variable that takes value 1 when $X \geq c$, that also highlight BISP treatment variable. Suppose h is bandwidth for the data that designates $c - h \leq X \geq c + h$. The following term represents for above and below the poverty score (cut-off) of the BISP program, that range of h. By specifying a thresh hold RDD estimates the impact of an intervention (BISP cash transfer). Where the RDD assumptions hold holding that around the specified cut-off the treatment is random. To identify the thresh hold of the nearest neighbors, the causal impact of the outcome for intervention can be estimated by calculating the difference in the outcome. That is for the control and treatment group respectively on the eligibility criteria (cut-off point).

Hence to compare the treatment and control group outcomes, (LTE) the local treatment effect would provide those estimations. Where (LTE) designates the effect of causality on outcome variables via dummy variables. Estimation of (ATE) consider as $T(for1) - T(for0) = lim \downarrow 0$ $E\ [Yi|Xi = c +] - lim \uparrow 0\ E\ [Yi|Xi = c +]$ simply written as: $E\ [Yi\ (1) - Yi\ (0)\ |\ X = c$ at the thresh hold it compares treatment with the control group. The Local Average treatment designates that the regression discontinuity design grips internal resilient validity to generate robust results of beneficiaries' impact evaluation. In the same scenario LTE for households that are away from the thresh hold also delivers external weak validity in positions of applicability [e.g. (Calonico, Cattaneo et al. 2019); Government of Pakistan, (2016); (Gertler and Giovagnoli 2014)].

Moreover, nonetheless, the Regression Discontinuity could be fuzzy or sharp, to concern BISP's evaluation. Where fuzzy regression discontinuity technique appears most spontaneous related to sharp RDD, due to the reason that few households that are below the eligibility thresh hold might not be getting the transfer payment. Somehow, some households are above the cut-off point of

16.17 receiving BISP's cash transfer, because of BISP's exceptional eligibility for households. This is the situation where the poverty score of BISP takes as an instrument that permits applying the fuzzy regression discontinuity design. For this purpose, the ultimate RDD specifying equation (3.2.2.2) can be written as follow:

$$Yi = \beta_0 + \lambda Ti + \beta_1(Xi - c) + \beta_1 T * (Xi - c) + \Sigma\beta_i Zi + \mu i \qquad (8)$$

In the following equation food security outcome Yi, which is further accumulated from 1) Per adult equivalent Kilocalories intake on daily biases, 2) availability of food items on weekly biases, 3) score of food security and 4) composite (FSI) food security index. On the other hand, Zi represents control variables of the base year, which are household head age and education, the ratio of females, and dependency ratio. Where the other classification is relevant to equation (3).

The underlying study applied fuzzy RDD to check the impact of the BISP's cash transfer on food security, by using the same data of BISP's impact evaluation reports (Government of Pakistan, 2016). Where (Ambler and De Brauw 2019) use the same fuzzy RDD design to evaluate BISP cash transfer on supply of labor for Pakistan, fuzzy RDD act as a local linear regression also contains bias correction of data-driven [7]. (Lee and Card 2008) proposed that fuzzy RDD designates triangular Kernel with regression analysis.

By applying RDD the bandwidth selection is an essential task, which specifies that to assign a range of values to assess treatment and control group for comparison such as PMT score for BISP. Where bandwidth for RDD offers (LATE) local average treatment effect. In the following studies, (Ambler and De Brauw 2019) applied 5 and 3 bandwidths, and the Government of Pakistan (2014, 2016) 5 bandwidths. The underlying study use fixed and optimal bandwidth 3 which is the optimal bandwidth provides a better scenario for the data of 2016, 2013, and 2014 due to the large sample.

Somehow there are some issues to be tested, for resolving those issues underlying study implement RDD. Which are assumption identification for verification of RDD, demonstrating

[7] In order to estimate fuzzy RDD, we implement "rdrobust" command on STATA software. This implementation provides bias-corrected confidence intervals (Cis) for local ATE at specified threshold for both sharp and fuzzy RD as described by Calonico et al., (2016).

that the existence of systematic differences within two groups (beneficiaries and non-beneficiaries) do not vary at the cut-off score of 16.17 discontinuously. Where no other social safety net must use the same cut-off if they do use the same the assumption would not remain sustained.

Another imperative task is to determine discontinuity, which specifies whether the targeting is planned or not. If it is not intended then the RDD will not effective, where theoretically evident that BISP targeting is planned. Because those households are eligible for the program which are below the poverty score of 16.17. where (Ambler and De Brauw 2019) prove it through graphical representation via different conventional tests. Somehow they find solid proof for discontinuity validation by using BISP cash transfer data[8].

One another task is to be a beneficiary of the program subject can manipulate poverty score in BISP scenario. Where subject manipulation to poverty score which is a forcing variable will invalidate Regression Discontinuity Design implantation. Somehow, the PMT score is assembled through 23 indicators, so logically households are unable to manipulate these indicators because the individual can only show themselves as poor. On the bases of the theoretical approach, the underlying study concludes that RDD is applicable for this evaluation. Where Ambler and de Brauw (2017, 2019) for manipulation problem diagnosing also used formal test, they found no evidential manipulation around the cut-off which validates Regression Discontinuity Design

[8] Ambler and de Brauw (2017, 2019) have tested by plotting graphs for 2013 and 2016 surveys by using fixed bandwidth of 5 on both sides of threshold.

empirical strategy [9]. So to test we apply RDD on assets of demographical households for the BISP baseline survey 2011 that was also used by Ambler and de Brauw (2019).

A set of food outcomes which are food stability, food diversity, a composite index of food security, and calorie intake of control and treatment groups in the base year 2011, show a no significant difference for recipients and non-recipients. whereas discontinuity in food outcome (food diversity, food security, and stability) is evaluated for both cross-sectional and panel households survey baseline of 2016. Where the underlying paper implements the following strategy, first applying fuzzy RDD to following the specified bandwidth with follow-up years 2013 and 2016 to estimate food diversity to capture food quality. Second, apply the same technique to check the impact of BISP cash transfer on the daily calorie intake of households. Where the same technique applies to the food group and weekly stability for each group. In the last, to estimate the impact of cash transfer of BISP on the food security index which comprises food availability, accessibility, and stability.

5.2.4.1 **Strategy of pooling data**:

To check the impact of BISP cash transfer the important task is to pool the survey data of BISP in four waves. The underlying model is used for the data pooling to apply the household fixed effect.

$$logit\ Yh, i, t = \beta i + \alpha 1 BISP\ h, i, t + \Sigma \beta i Z i, t + \mu i, t \qquad (9)$$

[9] We do not go for doing applying it. Because, Ambler and de Brauw 2017, 2019) have applied test of density of baseline variables that are not expected to be impacted by BISP on same dataset. The density of those baseline variables should be continuous through the eligibility cut-off. If this is not the case. we shall be concerned that RDD estimates are biased due to selection on such variables. In order to test it. they apply RDD by using fixed bandwidth of S on asset accumulation, household profile related variables such as family size, dependency ratio, and age composition in baseline 2O11.

The above equation shows the same variable of the outcome as considered in the RDD equation (4)**,** whereas the variable of BISP shows a binary indication of the variable with a beneficiary and non-beneficiary status of the individual. The Zi, t represents household characteristics with a ratio of females, size of family along with age, gender, and education of households.

5.2.5 Difference-in-Difference:

Differences-in-differences is a quasi-experimental design which applied to sets of group means in cases, when groups are exposed to the causing variable of interest and others are not. The simple DID design might be deceptive when it does not justify time-invariant properties. It means that treatment and control groups be similar in characteristics. Somehow, the error term is likely to be more correlated in post and pre-treatment scenarios. Whereas the underlying study used fixed effect with DID (Difference-in-Difference) control for observed and unobserved confounders. That offers more reliability for necessary assumptions to calculate spurious unbiased causal impact (Iqbal, Farooq et al. 2021). Which is apparent and often at the slightest casually plausible, and well-suited to assessing the effect of sharp changes in government policy or the impact of a program. (Lester 1946) applied the differences-in-differences design to identify the impact of employment on the lowest wages[10]. The DID design is described here using to check the impact of BISP's cash transfer on food security, a follow-up year's baseline survey is used for the estimation.

The underlying study evaluates the impact of the BISP program as a treatment on outcome Y

[10] The DD method goes by different names in different fields. Psychologist Campbell (1969) calls it the "nonequivalent control-group pretest-posttest design."

(Food Security), where the treatment status T = 0,1, here 1 represent the individual who received treatment (BISP's Beneficiary),0 is otherwise non-beneficiary. Whereas t = 1,0 highlight the period, here (1) indicate the time when the group received treatment (post treatment). On the other hand, 0 is the pre-treatment period before when the group individual did not receive treatment. In the underlying study, the Outcome variable Yi is sculpted by the following equation.

$$\mathrm{Yi} = \beta 0 + \beta 1\mathrm{Ti} + \beta 2\mathrm{ti} + \beta 3\ (\mathrm{Ti} \cdot \mathrm{ti}) + \varepsilon \mathrm{i} \qquad (10)$$

Here β0, β1, β2, and β3 are the coefficients that are unknown parameters, where εi is the error term which is random and unobserved and contains all determinants of Yi that model omits. In the above equation, the coefficients interpretations are. β_0 = constant term β_1 = permanent average difference between treatment and control group β_2 = time trend β_3 = exact effect of treatment. The evaluation of the program aims to sort out the best estimate of β_3 from the data available to us. Where the criteria for the best estimator is to be unbiased that explained that on average the estimate should be accurate.[11] The Difference-in-Difference estimator needs to hold the following assumptions[12].

1. Assumption of Consistency (The treatment status for diff-in-diff of a unit can vary over time).
2. Assumption of Parallel trend (In the absence of intervention difference between the control group and treatment group will be constant over the time).
3. Assumption of Positivity (It means that for a specific value of "X" the treatment is not determinant.

[11] https://eml.berkeley.edu/~webfac/saez/e131_s04/diff.pdf
[12] https://diff.healthpolicydatascience.org/

Where the difference in difference estimator is equal to the difference in average outcome in the treatment group pre and post-treatment, subtract from the difference in average outcome in control group pre and post treatment. Equation of the diff-in-diff write in the following form:

$$\delta_{DD} = \bar{Y}_1 T - \bar{Y}_0 T - (\bar{Y}_1 c - \bar{Y}_0 c) \qquad (11)$$

For unbiased estimation we should taking the expectation of the diff-in-diff estimator.

5.3 Inverse Probability Weighting Regression Adjustment (IPWRA):

To evaluate the impact of BISP cash transfer on food security the underlying study applied the Inverse Probability Weighting Regression Adjustment (IPWRA). The term treatment effect designates the average causal effect of a binary variable (0,1) on the outcome variable for a policy interest[13]. Impact evaluation needs revelation to adopt treatment which should be assigned randomly, and between treatment and control group the stimulus of observable and unobservable properties is similar that lead deferential impact to treatment (Shiferaw, Kassie et al. 2014). The underlying study used the data (BISP's baseline survey) to analyze the impact of cash transfers on household food security. Where to apply this model the study is to go through three measurements to find out the results. The underlying study estimates the (ATE) Average Treatment Effect, (ATET) which is the Average Treatment Effect of the Treated and (POMs) that Potential Outcome Means. In the case of binary treatment, the t=1 assign that individual take treatment (beneficiary), t=0 otherwise show no treatment for the individual. The potential

13 https://economics.mit.edu/files/32#:~:text=Treatment%20effects%20can%20be%20estimated,of%20scientific%20or %20policy%20interest.

outcome is denoted by Yi1 and Yi0, which are the realization of the random variables Y1 and Y0. So the parameters of interest should be defined as.

1. $ATE = E\ (Y1i - Y0i)$ for the average treatment of the population, E(.) is the expected value for the outcome, Y1 show if the strategy adopted Y0 for the otherwise not adopted strategy.
2. $ATET = E\ (Y1i - Y0i|t = 1)$ for the average treatment effect on treated, for those who received treatment.
3. $POMt = E(Yt)$ was used for the average potential outcome for treatment level t.

The underlying study uses the technique is the counterfactual framework used by (Rubin and (Giarman 1947) that followed to estimate the causation in observation and experimental studies [cited in (Henderson, Louis et al. 2016)]. The technique of 'Treatment Effect" is used to solve the problem of causal inference and what would they have been for not treated and exposed to treatment. By combining both the weighting and regression estimator (IPWRA) double-robust inverse-probability-weighted regression-adjusted, overcome the problem of causal impact and strategy adaptation to find out the actual value and counterfactual results [(Imbens and Wooldridge 2009); cited by (Henderson, Louis et al. 2016)]. To apply (IPWRA) technique which identifies the observed outcome variable Y_1i and Y_0i in a situation when t=0,1. In the mathematical form, we can write it $yi = (1 - t)\ y_0 + ty_1$, the outcome model function can be written as:

$$y_0 = x\beta_0 + {}_0i \qquad \text{if } t = 0 \qquad (12)$$

$$y_1 = x\beta_1 + {}_1i \qquad \text{if } t = 1 \qquad (13)$$

In the above equations, y_0 and y_1 represents outcome variables for food security for the beneficiary and non-beneficiary respectively. Where x denotes the vector of covariates, β_0, and β_1 denote the parameters of the estimator. In the same equation, $_0$ and $_1$ represents error term that is not linked with x, and $x\beta i$ are predictable components where i are unobservable.

In the underlying study the treatment assignment is inscribed as;

$$\mathrm{t} = \{1, \text{if } \mathrm{z}\gamma + \eta > 0{,}0 \text{ is the otherwise}\}$$

In the above equation z indicates the covariates vector, γ represents the estimated unknown coefficient vector. Where η describes the unobservable error term which not linked to x or z, here $zi\,\gamma$ are predictable components η is the unobservable error term. To applying the treatment effect model it requires convinced assumptions which as [Bordos, Csillag, and Scharle (n.d.)]:

1) The criterion of un-confoundedness, describe that the treated and untreated potential outcome do not govern by treatment when acclimatized on covariates. This specific assumption facilitates the combination of regression adjustment and the inverse probability weighting method.
2) Where the overlap assumption clarifies that every individual is positively probable to achieve treatment, for precise estimate counterfactual we match treated subject to untreated.
3) In the independent and identical distribution, the sampling assumption describes that the treatment status and potential outcome of every individual are unrelated to the rest of the individuals in the population.

The first assumption executes restrictions on the error terms covariance matrix $_{0}$, 1, and η [Ahmed, et al. (2016)].

Chapter 06
Results and Discussion

This chapter is furnished with discussion on empirically obtained results from the application of Inverse Probability Weighting Regression Adjustment (IPWRA) and difference-in-discontinuity. Initially, this chapter weaves up discussion the results obtained from the Inverse IPWRA, which entails detailed description of findings. After that, the discussion on findings obtained from the implementation of Regression Discontinuity Design (RDD) and Difference-in-Discontinuity (DiD) has been hatched, which provides us comprehensive comparison between the results of these techniques and IPWRA.

6.1 Results from Inverse Probability Weighting Regression Adjustment (IPWRA):

We have estimated the impacts of the BISP cash transfer on household food security by applying IPWRA, which provides us counterfactual analysis. The comprehensive description of the findings is given as follows.

6.1.1 Household Food Security and BISP Cash Transfer:

To highlight the impact of BISP cash transfer on food security, we estimated the Potential Outcome Mean (POM), Average Treatment Effect (ATE), and Average Treatment Effect on Treated (ATET), these measures suggest the impact of BISP cash transfer on food security through counterfactual analysis. We have used household-specific covariates along with the BISP variables. Such variables include the size of household, sex of head, age of head, matriculation, intermediate, and above intermediate education, female ratio, distance bus stop km, distance market km, and regional variables. We have used pooled and cross-sectional data for estimation.

The estimated results obtained from pooled data is indicating that other things remain the same, the potential outcome mean of BISP recipients are higher than the control group (table-6.1). The difference between both (beneficiary and non-beneficiary) is called the average treatment effect score which is found 0.017, which means BISP recipients are conceding higher calorie intakes by 1 percent. It demonstrates that BISP is supporting the households to sustain food security for a longer period. Alternatively, BISP is helping households to avoid chronic food insecurity in terms of calorie deficiency (table-6.1).

Table 6.1: Impact of BISP on Calories Intake: Average Treatment Effect (ATE)

	POM (1)	**POM (0)**	**POM (1)-POM (0)=ATE**
Year	Beneficiary	Non-Beneficiary	Average Treatment Effect
Pooled Sample	5.86387*** (0.1468)	5.846172*** (0.1453)	0.0177078** (0.0078)
Follow-up 2013	7.6551038*** (0.020186)	7.604564*** (0.020186)	0.0505398* (0.018805)
Follow-up 2014	7.6186269*** (0.014694)	7.596738*** (0.014694)	0.0218889* (0.012837)
Follow-up 2016	2.0244842*** (0.001922)	2.023129*** (0.001922)	0.0013552** (0.000681)

Note: POM=Potential Outcome Mean; while
Pooled sample contains (baseline 2011, follow-ups 2013, 2014, and 2016
() =standard errors, while p<0.1=*, p<0.05=**, and p<0.01=*** Dependent Variable is log of calorie intakes

If we break the sample into a cross-section, then again we have found the significant impact of BISP on improving the calorie intake of the households. For the follow-up survey in 2013, the score of POM (1) for BISP beneficiaries is estimated as 7.65, while 7.60 for no beneficiary. The

gap between these two is called the average treatment effect (ATE). The ATE is found at 0.50 which means a 5 percent increase in calorie intake among the beneficiaries, while
ATE during 2014 is found at 0.021 which means a 2 percent improvement in calorie intake (table 6.1). Likewise, during the survey of 2016, the score declined up to 0.001 which means less than 1 percent increase in calorie intake of the BISP recipients. By concluding these findings, the cash transfer has a significant impact on securing food outcomes for the households but these impacts are going to weaken over time as the decline of the coefficients of ATE over time has suggested.

The other ways to investigate the impacts are what could have happened to the BISP beneficiaries if they have not been given cash transfers. For that purpose, we have computed the average treatment effect on treated (ATET) which is given table-6.2. ATET is computed on the sub-sample of the survey means for those who are BISP beneficiaries. For that, it works like treating the beneficiary as a control group and then comparing it with the treated. The score of ATET for pooled and cross-section data has determined that BISP recipients could have not been better and could be worse off if the BISP cash transfers were not given to them (see positive coefficients of ATET in table-6.2).

Suppose if all the BISP receiver households were to become non-receiver of the program, then the average outcome be (5.22416) which indicates that the BISP cash receiver to be better wellbeing than the non-receiver. Even, if had they not received the package of BISP they still would have been comparatively additional kilocalories intakes than the genuine non-receiver in the population size. If all BISP cash receiver households' subsamples become non-receiver, the Average Treatment Effect on Treated (0.0205) is approximately equal to the Average Treatment Effect (0.0177078) estimate.

Table 6.2: BISP and Calorie Intakes: Average Treatment Effect on Treated (ATET)

	POM (0)	POM (1)	ATET
Year	Non-Beneficiary	Beneficiary	Average Treatment Effect on Treated
Pooled Sample	5.2036*** (0.1863)	5.22416** (0.006)	0.0205*** (0.0067)
Follow-up 2013	7.585337*** (0.021339)	7.6387386*** (0.01836)	0.0534016*** (0.01836)
Follow-up 2014	7.578188*** (0.015533)	7.6070463*** (0.012243)	0.0288583*** (0.012243)
Follow-up 2016	2.022181*** (0.001923)	2.0235893** (0.000696)	0.0014083** (0.000696)
Note: POM=Potential Outcome Mean; while Pooled sample contains (baseline 2011, follow-ups 2013, 2014, and 2016) ()=standard errors, while p<0.1=*, p<0.05=**, and p<0.01=***			

Where the results indicate the fact that the non-receiver pointedly lower food security than the receiver of BISP cash transfer, while the non-receiver experience small POM means i.e. 0.0205 which is statistically significant, perhaps due to the least variation in the sample. More precisely it explains that those households who receive BISP packages were more food secure than that if they were non-beneficiary.

Table 6.3 proposes that (POM 1) and (POM 0) are the combinations of the beneficiaries and non-beneficiaries. Where the difference between these two is to estimate the well-being when the household received BISP cash. The result given the table 6.2 for the impact of the cash program indicates that (POM) for households who are the beneficiaries of the program is higher than those households who are non-beneficiaries. The (POM 1) for beneficiaries was found more positive and highly significant (1.7569883) on other hand (POM 0) for non-beneficiaries is positive and significant (1.756563) but less than the beneficiaries.

Table 6.3: Impact of BISP on Daily Per Food Diversity: Treatment Regression Adjustment

	POM (1)	POM (0)	POM (1)-POM (0)=ATE
Year	Beneficiary	Non-Beneficiary	Average Treatment Effect
Pooled Sample	1.7569883*** (0.008745)	1.756563*** (0.008745)	0.0004253* (0.005366)
Follow-up 2013	1.7544714*** (0.015646)	1.74094*** (0.015646)	0.0135314* (0.011118)
Follow-up 2014	1.8047917*** (0.009139)	1.803386*** (0.009139)	0.0014057* (0.008664)
Follow-up 2016	1.7815933*** (0.011454)	1.783171*** (0.011454)	-0.0015777* (0.006167)

Note: POM=Potential Outcome Mean; while
Pooled sample contains (baseline 2011, follow-ups 2013, 2014, and 2016)
()=standard errors, while p<0.1=*, p<0.05=**, and p<0.01=***

The significant difference in the potential outcome of the mean (POM) explains that households that are beneficiaries of BISP are more food secure in food diversity as compared to others who are non-beneficiaries of the BISP. Where the Average Treatment Effect explains an average of the population which designates the difference between the outcome of the whole population who receive the cash and those who are non-receiver of the package of BISP. The ATE measure is (0.0004253) with the positive sign which is highly significant describing that households who receive the package are significantly more food diverse as compared to those who are not. However, it is to be noted that households are more secure in food to receive the package of BISP cash transfer.

Where table 6.4 shows (ATET) average treatment effect on treated household estimations. Table highlights that if the receiver household of the BISP package had not received the package then what would have been their outcome well-being condition of food security.

Table 6.4: Impact of BISP on Food Diversity: Treatment Regression Adjustment

	POM (0)	**POM (1)**	**ATET**
Year	Non-Beneficiary	Beneficiary	Average Treatment Effect on Treated
Pooled Sample	1.761684*** (0.008506)	1.7619165** (0.005)	0.0002325*** (0.004945)
Follow-up 2013	1.741177*** (0.015453)	1.7557179*** (0.011)	0.0145409*** (0.010632)
Follow-up 2014	1.807462*** (0.008781)	1.8071779*** (0.0081)	-0.0002841*** (0.008077)
Follow-up 2016	1.783314*** (0.011432)	1.7825827*** (0.005)	-0.0007313*** (0.006236)
Note: POM=Potential Outcome Mean; while Pooled sample contains (baseline 2011, follow-ups 2013, 2014, and 2016) ()=standard errors, while p<0.1=*, p<0.05=**, and p<0.01=***			

Where table 6.4 shows (ATET) average treatment effect on treated household estimations. This highlights that if the receiver household of the BISP package had not received the package then what would have been their outcome well-being condition of food security. Suppose if all the BISP receiver households were to become non-receiver of the program, then the average outcome be (1.7619165) which indicates that the BISP cash receiver to be better well-being than the non-receiver. Even if they had not received the package of BISP they still would have been comparatively additional food diverse than the genuine non-receiver in the population size. If all

BISP cash receiver households' subsamples become non-receiver, the Average Treatment Effect on Treated (0.0002325) is approximately equal to the Average Treatment Effect (0.0004253) estimate. Where results indicate the fact that the non-receiver pointedly lower food secure than the receiver of BISP cash transfer, while the non-receiver experience small POM means i.e. 0.0002325 which is statistically positive and insignificant, perhaps due to the least variation in the sample. More precisely it explains that those households who receive the BISP package were previously more food diverse than that if they were non-beneficiary.

The ATE, ATET, and POMs resulted from values from the model that uses the BISP cash transfer intervention that also defects positively significant impact on daily kilocalories intake as well on daily food diversity suggesting that those households who receive the package of BISP are more food secure is compare those who not receive this cash. Where the difference between receiver and non-receiver is significant and average treatment effects are significantly positive for the receiver. Somehow ATET explains that if treated individuals became control or non-treated so what will impact households' wellbeing.

6.1.2 Household Specific Covariates: Beneficiary versus Non-Beneficiary:

While the elements of daily per adult kilocalories intake of beneficiary and non-beneficiary are described in table 6.5. Where potential outcome model in Equation 1,2 Appling treatment effect technique using regression-adjustment 'teffect' command in Stata 17 which pooled model outcome and status of treatment. The estimated parameters are stated correspondingly in tables 6.5 and 6.8.

Somehow more of the parameters in outcome estimations for BISP cash transfer are statistically significant and describe BISP cash transfer as unlimited similar to the route equation of the receiver and non-receiver. While the study did not sort out significant withdrawal in objects of originating a complete conclusion. For that purpose, (the magnitude and signs) of parameter estimates are essential to understanding the results.

Table 6.5: Average treatment effect; Daily per Adult kilocalories intake

	Pooled		2013		2014		2016	
Status	**Receiver**	**Non-Receiver**	**Receiver**	**Non-Receiver**	**Receiver**	**Non-Receiver**	**Receiver**	**Non-Receiver**
Size of household	-0.015***	-0.023***	-0.032***	-0.034**	-0.026**	-0.0297**	-0.002***	-0.0032***
Sex of head	-0.014*	-0.031***	-0.043*	-0.07***	-0.058**	-0.0374**	-0.006**	-0.0043*
Age of head	0.00073***	0.00063***	0.0013*	0.0016**	0.0022**	0.0007**	0.00008*	0.000043
Matriculation Edu	-0.0064*	0.0066*	-0.035*	-0.009*	-0.0273*	-0.007	0.000156	0.005***
Intermediate Edu	0.0269*	0.0449**	0.0085*	0.108**	0.0263*	0.06*	0.0025	0.0066**
Above inter Edu	0.0163***	0.0133**	0.0166*	0.016*	0.0275*	0.004	0.0017*	0.0011
Female ratio	-0.0005*	-0.0044*	0.0067*	-0.013**	-0.0106*	-0.007*	0.0003	0.0005*
Distance bus stop	0.0044*	0.0074***	-0.0002**	-1.16e-06	0.00007*	-8.33E-06	0.000013	-7.74E-06
Distance market km	-0.00008**	-0.00002*	0.00008*	-0.0003*	0.0002**	0.00011*	-0.000054	-0.000029
District region1	0.00015***	0.000097*	-0.096***	-0.07***	-0.128**	-0.071***	-0.0060**	-0.009***
_cons	7.612***	7.681***	7.87***	7.861***	7.8***	7.83***	2.050***	2.051***
Note: p<0.1=*, p<0.05=**, and p<0.01=***								

Where the results describe that size of household, sex of head, age of head, matriculation Edu, intermediate Edu, above inter Edu, female ratio, distance bus stop km, distance market km, and district region1 are the status dynamics which increase the food security of households where the impact of these dynamics are statistically significant.

Table 6.5 describes the results of the overall average treatment effect for daily per adult kilocalories intake, which indicates the difference between beneficiaries and non-beneficiaries. The status dynamics which show a negative but statistically significant association to food security are the size of households, sex of households, matriculation education, female ratio, and distance from the market in km. But the negative impact of these dynamics is significantly more negative numbers for non-beneficiary compared to beneficiaries. On the other hand, age of household head, intermediate and above inter education, distance from the bus stop and district region show statistically positive and significant impact on daily kilocalories intake. But for beneficiaries, the results show significantly more positive numbers compared to non-beneficiaries. Somehow in different follow-up years, the results of these statuses are shown as non-significant figures also, but the signs do indicate the positive effect on those who receive the package of BISP cash transfer.

Table 6.6: Average treatment effect; Daily per Adult food diversity

	pooled		**2013**		**2014**		**2016**	
Status	**Receiver**	**Non-Receiver**	**Receiver**	**Non-Receiver**	**Receiver**	**Non-Receiver**	**Receiver**	**Non-Receiver**
Size of household	0.006***	0.0082***	0.007***	0.01***	0.0075**	0.0097***	0.008***	0.0075***
Sex of head	-0.009	-0.0139	0.015	-0.017	-0.042**	-0.015*	-0.014	-0.0337**
Age of head	0.0006***	0.0008***	-4.24E-06	0.0006*	-0.00002	0.0004**	0.001***	0.0013***
Matriculation Edu	0.0095	0.032***	-0.027	0.05***	0.0083	0.014	0.0022	0.028*
Intermediate Edu	0.052***	0.050***	0.071*	0.090***	0.073*	0.033*	0.021	0.0186
Above inter Edu	0.0295***	0.038***	0.03**	0.018***	0.016*	0.032***	0.041***	0.0623***
Female ratio	-0.00106	-0.002	0.0015	-0.007*	-0.0064	-0.0018	-0.00033	0.0013
Distance bus stop	-0.0007***	-0.0001***	-0.0016**	-0.01*	-0.001**	-0.0001**	0.00060	-0.0001
Distance market km	-0.0000213	-4.20E-06	-0.000015	-0.00010	-1.16-e06	0.0001***	3.15E-08	0.0004
District region1	0.026**	0.033***	0.05**	0.06***	0.024*	0.04***	0.0036	-0.002
_cons	1.57***	1.574***	1.64***	1.63***	1.778***	1.69***	1.67***	1.65***
Note: p<0.1=*, p<0.05=**, and p<0.01=***								

Table 6.6 describes the results of the overall average treatment effect for daily per adult kilocalories intake, which indicates the difference between beneficiaries and non-beneficiaries. The status dynamics show negative but statistically significant associations to food diversity are sex of households, female ratio, distance bus stop km, and distance from the market in km. But the negative impact of these dynamics is significantly more negative numbers for non-beneficiary compared to beneficiaries. Whereas, Size of household, Age of head, age of household head, Matriculation, intermediate and above inter-education, and district region show statistically positive and significant impact on daily kilocalories intake. But for beneficiaries, the results show

significantly more positive numbers compared to non-beneficiaries. Somehow in different follow-up years, the results of these statuses are showing non-significant figures also, but the signs do indicate the positive effect on receiving the package of BISP cash transfer.

6.2 BISP Impact on Food Security: Regression Discontinuity Application:

This section of the underlying study tries to highlight the impact of BISP cash transfer through RDD with the confidence interval of data-driven base correction. Where resulted outcomes are attained by bandwidth 5 along with the approach of optimal bandwidth for Follow-ups (2013 and 2016), which were recommended by Ambler and de Brauw (2019).

In a follow-up in 2013, the results explored that BISP cash transfer shows a positive impact on Chronic food insecurity elevation. Where the estimated results are statistically significant with the bandwidth 5 around the cut-off. Which explored that beneficiaries of the BISP cash transfer nearby fixed bandwidth to show more food security compared with those who are away from the cut-off point as non-beneficiaries or controlled. Somehow, the results of the optimal bandwidth are not that much significant as bandwidth 5 is. The results are available below in table 6.7, where the results of the table show that BISP cash transfer has a positive impact on chronic food insecurity.

In a follow-up in 2016, the results explored that BISP cash transfer shows a significant impact with fixed bandwidth. Where the cross-section 2016 results explored that the BISP cash transfer has a strongly positive impact on chronic food insecurity elevation. Somehow, RDD calculates the local treatment effect near to cut-off point. That’s why positive sign indicates a more significant impact of the BISP cash transfer on the food insecurity outcome of the group who are treated as a match to the group who are controlled. The results of the 2016 follow-up are available below in table 6.8.

Table 6.7: Impact of BISP on Chronic Food Insecurity by applying RDD: Panel 2013

	Food Diversity	**Kilocalories intakes**
	Bandwidth (h=5)	
BISP Estimates of RDD	-0.6318 (0.4415)	0.2593** (0.085)
Sample size right of the cut-off	2932	
Sample size left of the cut-off	2256	
	MSE-optimal bandwidth	
BISP Estimates of RDD	-0.09518 (3.2154)	-0.63104 (2.3675)
Sample size right of the cut-off	938	896
Sample size left of the cut-off	906	843
Bandwidth (h)	1.336	1.24
Bandwidth bias (b)	2.185	2.082
Overall sample size	8159	
Sample size left of cut-off	5484	
Sample size right of cut-off	2666	

Note: Parenthesis Values represent Standard Error, which is obtained by PSUs Clustering p<0.1=*, p<0.05=**, and p<0.01=***
The baseline year 2011 variables are controlled that have Household size, Household sex, Household age, Matriculation Edu, Intermediate Edu, above inter Edu, Female ratio, Distance bus stop km, Distance market km, D-region1, Period, and the baseline outcome variable.

In able Table, 6.7 results of the RDD estimates for food diversity are showing statistically significant for both fixed with optimal bandwidth. Where the results expose that BISP cash transfers have no impact on food-diverse beneficiaries. However short term impact is insignificant for food diversity. Somehow the results show a positive and significant impact of BISP cash transfer on kilocalories intake with fixed bandwidth but insignificant for optimal bandwidth on the cut-off point.

In above Table 6.8 BISP cash transfers show a positively significant impact on food diversity as compared to the 2013 follow-up. Where the results of the RDD for both bandwidths fixed and optimal are found statistically significant. This also indicates that the 2016 follow-up are more strong results as compared to the 2013 follow-up.

Table 6.8: Results of BISP impact by applying RDD for 2016 follow-up

	Follow-up 2016	
	Food Diversity	**Kilocalories Intake**
	Bandwidth (h=5)	
Bias-corrected RD estimates	0.042** (0.0179)	0.038** (0.0189)
Sample size left of cut-off	4575	
Sample size right of cut-off	4972	
	MSE-optimal bandwidth	
Bias-corrected RD estimates	0.067** (0.01798)	0.063* (0.0332)
Sample size left of cut-off	1322	1059
Sample size right of cut-off	1093	850
Bandwidth (h)	1.148	0.763
Bandwidth bias (b)	2.179	1.752
Overall sample size	11323	
Sample size left of cut-off	6352	
Sample size right of cut-off	4972	

Note: Parenthesis Values represent Standard Error, which is obtained by PSUs Clustering p<0.1=*, p<0.05=**, and p<0.01=***
The baseline year 2011 variables are controlled that have Household size, Household sex, Household age, Matriculation Edu, Intermediate Edu, above inter Edu, Female ratio, Distance bus stop km, Distance market km, D-region1, Period, and the baseline outcome variable.

It also indicates that in 2016 follow-up beneficiaries of BISP cash transfer may shift towards quality food groups. On the other hand, results for kilocalories, and intakes are statistically positive and significant for cross-sectional 2016. Which are significant for both optimal and fixed bandwidth. From this, we can conclude that there is a strong positive effect of BISP cash transfer on kilocalories intakes.

6.3 BISP Impact through Difference-in-Discontinuity:

In this section of the study, we try to explain the impact of BISP cash transfer through Diff-in-Dis with the confidence interval based on data-driven correction. The Diff-in-Dis shows the difference between control and treatment with a cut-off point. Where resulted outcomes are attained by bandwidth 5 along with the approach of optimal bandwidth for Follow-ups (2013 and 2016), which were recommended by Ambler and de Brauw (2019).

In a Panel 2011 & 2013, the results explored that BISP cash transfer shows a positive impact on Chronic food insecurity elevation and show the comparison between 2011 and 2013. Where the estimated results are statistically significant with the bandwidth 5 around the cut-off. The results suggest the existence of iteration problem because the sample size in 2011 is more than in 2013. Where beneficiaries of the BISP cash transfer nearby fixed bandwidth to show more food secure compared with those who are away from the cut-off point as non-beneficiaries or controlled. The results are available below in table 6.9, where results of the table show that BISP cash transfer has a positive impact on chronic food insecurity.

In follow-up 2011 and 2016, the results explored that BISP cash transfer shows a significant impact with fixed bandwidth. The 2011 and 2016 follow-up results explored that the BISP cash transfer has a strongly positive impact on chronic food insecurity elevation. Somehow, Diff-in-Dis calculate the local treatment effect near to cut-off point. That’s why positive sign indicates a significant impact of the BISP cash transfer on the food insecurity outcome of the group who are treated as a match to the group who are controlled. The results of the 2011 and 2016 follow-up are available below in table 6.9. Where the same problem of iteration exists with more sample size in 2011 is compared to in 2016.

In panels 2011 & 2013 and follow-up 2011 & 2016 of Table 6.9, we assess whether the BISP cash transfer effect food security indicators which are kilocalories intake and food diversity. Whereas we find a statistically significant impact of BISP cash transfer on chronic food insecurity indicators, in results we find that food diversity is lower by 3% to positive 3.2% from 2011 & 2013 to 2011 & 2016. On another hand in the results, we find that daily kilocalories are lower by 3% to increase by 4% from 2011 & 2013 to 2011 & 2016. However short term impact is insignificant for food diversity. Somehow it shows a positive and significant impact of BISP cash transfer on kilocalories intake with fixed bandwidth.

Table 6.9: Impact of BISP cash transfer on chronic food insecurity, Diff-in-Dis estimates

	Panel (2011 & 2013)	
	Food Diversity	**Kilocalories Intake**
	Bandwidth (h=5)	
Bias-corrected Dif-in-Dis estimates	0.0311 (0.0423)	0.0347*** (0.009)
Robust	0.0253 (0.0214)	0.0052* (0.0023)
Baseline 2011		
Sample size left of cut-off	3368	
Sample size right of cut-off	3006	
Follow-up 2013		
Sample size left of cut-off	2932	
Sample size right of cut-off	2256	
	Panel (2011 & 2016)	
	Food Diversity	**Kilocalories Intake**
	Bandwidth (h=5)	
Bias-corrected Dif-in-Dis estimates	0.0332 (0.0221)	0.00437** (0.00171)
Robust	0.0372 (0.0324)	0.0052*** (0.0021)
Baseline 2011		
Sample size left of cut-off	3368	
Sample size right of cut-off	3006	
Follow-up 2016		
Sample size left of cut-off	1228	
Sample size right of cut-off	998	

Note: Parenthesis Values represent Standard Error, which is obtained by PSUs Clustering p<0.1=*, p<0.05=**, and p<0.01=***
The baseline year 2011 variables are controlled that have Household size, Household sex, Household age, Matriculation Edu, Intermediate Edu, above inter Edu, Female ratio, Distance bus stop km, Distance market km, D-region1, Period, and the baseline outcome variable.

2016 follow up are more strong results as compared 2013 follow-up. It also indicates that in 2016 follow-up beneficiaries of BISP cash transfer may shift towards quality food groups. On the other hand, results for kilocalories, and intakes are statistically positive and significant for cross-sectional 2016. Which are significant for both optimal and fixed bandwidth. From this, we can conclude that there is a strong positive effect of BISP cash transfer on kilocalories intakes.

6.4 Remarks on Comparison between Difference-in-Discontinuity and IPWRA:

In this section of the study, we build an explanatory write-up about the comparison of robustness of the results between the Diff-in-Dis and IPWRA Treatment Effect Model. From the above results, we come to conclude that Treatment Effect Model is more fixable and provides more detailed information about the impact evaluation of a program compared to the Diff-in-Dis design. For further explanation, it indicates that other things remain the same the difference between both (beneficiary and non-beneficiary) is the average treatment effect score. On other hand, ATET estimates the impacts that what would be happened to the BISP beneficiaries if they have not been given cash transfers. It works like treating the beneficiary as the control group and then comparing it with the treated. Somehow, in the Treatment effect model, we come to conclude that over time the magnitude of BISP cash transfer is declining but is still positive. Though BISP cash transfer plays an important role to elevate chronic food security due to inflationary shocks the impact of BISP is not meditating over the time period.

Table 6.9: Impact of BISP on Calorie Intakes: Average Treatment Effect (ATE)

	IPWRA	RDD (H=5)	Diff-in-Discontinuity H=5
Pooled Sample	0.0177** (0.0078)		0.00695** (0.0032)
Follow-up 2013	0.0505** (0.018)	0.2593** (0.085)	0.0347*** (0.009)
Follow-up 2014	0.0218* (0.012)		
Follow-up 2016	0.0013** (0.000681)	0.038** (0.0189)	0.00437** (0.00171)

Note: Parenthesis Values represent Standard Error, which is obtained by PSUs Clustering p<0.1=*, p<0.05=**, and p<0.01=***
The baseline year 2011 variables are controlled that have Household size, Household sex, Household age, Matriculation Edu, Intermediate Edu, above inter Edu, Female ratio, Distance bus stop km, Distance market km, D-region1, Period, and the baseline outcome variable.

Table 6.9 depicts the results of Average Treatment Effect (ATE) estimates obtained from IPWRA, RDD, Diff-in-Discontinuity techniques for comparison purpose to highlight impact of BISP cash transfer on Calorie Intakes. The results show that the average treatment effect estimates are statistically significant for both methodologies. But overall this impact is going to weaken over time as the decline of the coefficients of ATE over time. Somehow the IPWRA shows some flexible estimates as compared to RDD, DID in a sense that IPWRA validated all the samples (observed and unobserved) of the survey data. Due to manipulation of unobserved samples the results may show low estimate is compared to the other technique. But RDD and DID take subsamples of the data means that the chunk of samples is very low around the cut-off due to eligibility criteria. Though in 2016 the estimator of RRD and DID is better than IPWRA because the RDD and DiD highlights the estimate for few samples in a chunk around the cutoff.

Table 6.10: Impact of BISP on Food Diversity Score: Average Treatment Effect (ATE)

	IPWRA	RDD (H=5)	Diff-in-Discontinuity H=5
Pooled Sample	0.0004253* (0.005366)		0.0165*** (0.0060)
Follow-up 2013	0.0135314* (0.011118)	-0.6318 (0.4415)	0.0311 (0.0423)
Follow-up 2014	0.0014057* (0.008664)		
Follow-up 2016	-0.0015777* (0.006167)	0.042** (0.0179)	0.0372 (0.0221)
Note: Parenthesis Values represent Standard Error, which is obtained by PSUs Clustering p<0.1=*, p<0.05=**, and p<0.01=*** The baseline year 2011 variables are controlled that have Household size, Household sex, Household age, Matriculation Edu, Intermediate Edu, above inter Edu, Female ratio, Distance bus stop km, Distance market km, D-region1, Period, and the baseline outcome variable.			

Table 6.10 depicts the results of Average Treatment Effect (ATE) estimates obtained from IPWRA, RDD, Diff-in-Discontinuity techniques for comparison purpose to highlight impact of BISP cash transfer on Food Diversity Score. Where the results show that the average treatment effect estimates are statistically significant for IPWRA, but not for Diff-in-Discontinuity Follow ups. Overall this impact is going to weaken over time as the decline of the coefficients of ATE over time. Somehow the IPWRA shows some flexible estimates as compared to RDD, DID in a sense that IPWRA validated all the samples (observed and unobserved) of the survey data. Due to manipulation of unobserved samples the results may show low estimate but significant estimates is compared to the other technique (RDD, Diff-in-Discontinuity).

The Difference-in-Discontinuity technique also provides the same analysis of the treatment effect to identify the difference between treated and untreated. But specifically, the Difference-in-

Discontinuity design work as a quasi-experiment and only captures the estimates of sample size. Being a quasi-experiment the Diff-in-Dis design work with a specific bandwidth from which we cannot explore the analyses broadly. It means that if we want to conduct analysis suppose on a provincial level analysis the model can create an issue of the observation to highlight the impact of evolution. Because near the cut-off score along with fixed bandwidth the reaming observation is considerably less whenever the sample fragmented into a provincial level.

Chapter 07
Qualitative Analysis: Food Insecurity

7.1 Fact and Figures:

Worldwide food insecurity risk is the main consideration by policymakers, billions of people around the globe are food insecure, in which Asia, the pacific islands, and Sub-Saharan Africa experience the worst food-secure situation. Somehow Pakistan is also one of those most awful impacted countries whose population is chronically food insecure. Where the recent price hike in food items severely impacted that part of the population which is below the poverty line with an income of 2$ a day. Around 38% of the population of Pakistan is considering food insecure from 2021-31 (International Food Security Assessment by the US Department of Agriculture). Where about 16 % of the population is considered moderate or severe food insecure (Pakistan Bureau of Statistics). On the other hand, around 18 % of the children age 5 undergo malnutrition, and at the same age of 5 around 40 % of children are diagnosed with stunted growth[14].

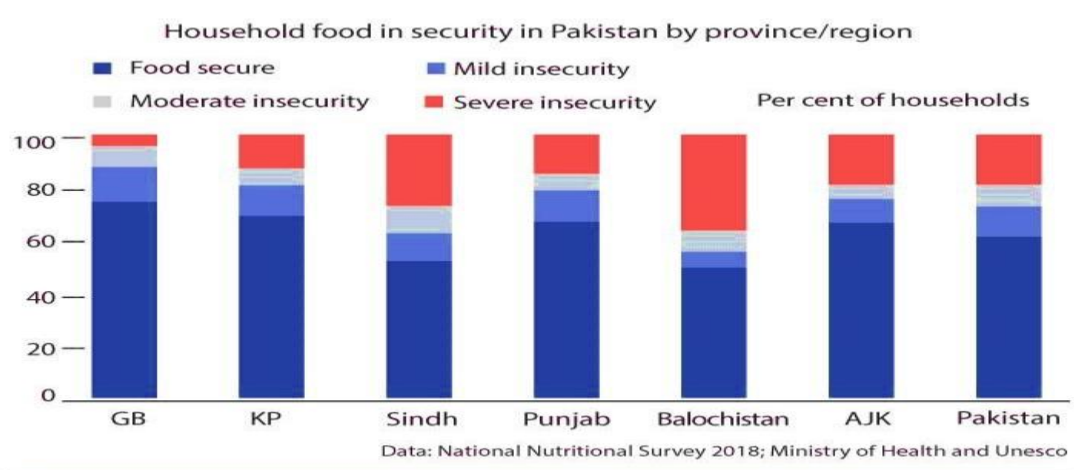

Figure 7.1: Household food insecurity in Pakistan by region/provinces

[14] https://issi.org.pk/issue-brief-on-food-security-challenges-for-pakistan/#_ftn1

Although the term food security is flexible according to food and agriculture organization (FAO) accept that food security exists when people of a country every time have an easy approach to safe and healthy food to meet their dietary needs. According Ministry of Health and Unicef's National Nutritional Survey 2018 about 63.1% of the population's households are considered a portion of food security. Where 36.9 % of the population households are categorized as a portion food insecure, which 18.3 % considered severe food insecure, 11.1 % considered mild and 7.6% considered moderate food insecure. Above figure 7.1 shows that provinces KPK and GB consider more food secure as compared to other provinces, in which Sindh and Balochistan are less food secure[15].

7.2 Budgetary Allocation on Food Security:

The total amount of PKR 1913 billion was allocated to pro-poor programs such as education, health, building infrastructure, natural calamities, and cash grants to ultra-poor households. The pro-poor expenditures by incumbent governments continued to increase, and during 2019-20, PKR 3447.35 billion. Specifically, government expenditures on disbursement of cash grants also continued to be scaling up. Figure-2 exhibits that PKR 15.85 billion was allocated for cash grants in 2008-09, while PKR 139.29 billion was allocated for the year 2020-21. Nonetheless, to cushion against the disastrous impacts of COVID-19, PKR 232.37 billion has been allocated.

From above-discussion unleashes three important outcomes: i) declining trends of poverty over the years (see figure-1), ii) increasing trend of budgetary allocation on cash transfers or social

[15] https://www.sbp.org.pk/reports/quarterly/fy19/Third/Special-Section-2.pdf

safety nets by the government of Pakistan (see figure-2), and the increasing implementation of the social safety nets are helping to reduce poverty from Pakistan[16].

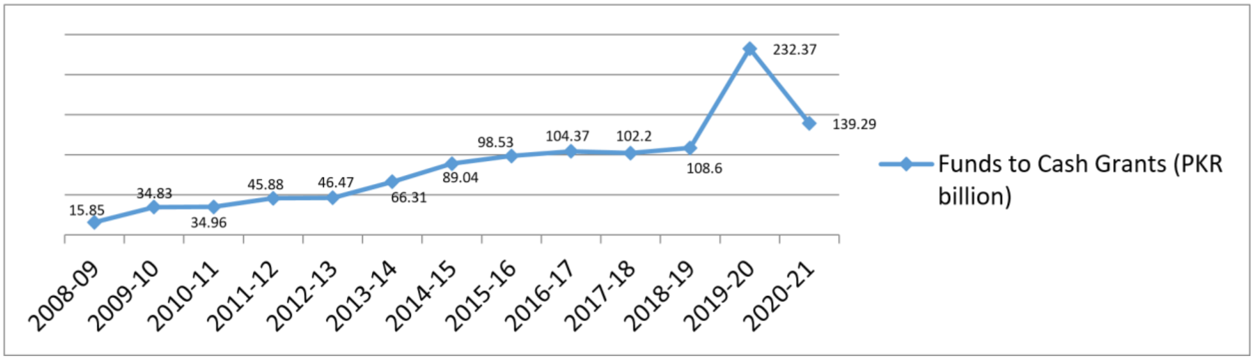

Figure 7.2: Federal funds on poor cash grants: Source: Pakistan Economic Survey (2020 -21**)** during the fiscal year of 2019-20 (Pakistan Economic Survey (2020-21)[17].

Hence, we can conclude that during the last decade the government of Pakistan has shown its priorities to deal with poverty by spending more on poverty alleviation programs.

7.3 Key Initiatives:

Globally, during this phase, the demand for the implementation of conditional and unconditional cash transfers has increased tremendously in developing countries to make their citizens more resilient against idiosyncratic and covariate shocks. Hence, Pakistan also implemented major cash transfer programs and other social safety nets to reduce poverty such as Pakistan Poverty Alleviation Fund (PPAF), Benazir Income Support Program (BISP), and Ehsas cash transfers. A brief description of these programs is given as follows.

[16] Javed, A., Ahmed, V., & Amal, B. K. (2021). The Social safety nets and poverty alleviation in Pakistan: an evaluation of livelihood enhancement and protection Programme. *Britain International of Humanities and Social Sciences (BIoHS) Journal*, *3*(1), 21-36.
Ijaz, U. (2021). Impact of Benazir Income Support Program (BISP) on consumption, health and education. *Economic consultant*, (4 (36)), 42-50.

[17] Government of Pakistan. (2020-21). Pakistan Economic Survey: Government of Pakistan, Finance Division.

Pakistan Poverty Alleviation Fund (PPAF): The PPAF was established in 2000, and is being carried out by 134 non-governmental partner organizations. The overall aim of the PPAF is to improve the quality of living standards of the poor and marginalized people from all over Pakistan. Its specific goals include: i) poverty reduction—extreme hunger, ii) increasing women empowerment and gender equality, iii) obtaining universal primary education, iv) improving the mental health, v) reducing the child mortality, and vi) to build and make stronger the community-based and NGOs-based institution. There are multiple programs working under PPAF, which are contributing in food security related agenda such as Growth for Rural Advancement and Sustainable Progress (GRASP), Livelihood Support and Promotion of Small Community Infrastructure (LACIP) and Enhancing Food Security through Strategic Interventions in Agriculture. Primarily, PPAF is helping country to implement poverty reduction agenda through provision of micro-credit, health and education, water, and building capacity through employment generating-strategies. Since the PPAF came into being and to the date, the institution has disbursed an amount of virtually PKR 228 billion to its partner organizations in around 147 districts across the whole Pakistan. Moreover, total of 8.4 million loans have been allocated to women particularly rural females. All these grants are found contributing significantly in achieving the poverty reduction goal (Government of Pakistan, 2020-21). Following are the key achievements of the PPAF.

i. According to Pakistan Economic Survey (2019-20), the PPAF has completed 38,300 health, education, water, and infrastructure related projects.

ii. The PPAF has formed 440,000 credit groups, and 134,500 community-based organizations.

iii. (GRASP) project provide income and employment in live stocks and horticulture for 22 districts in Sindh and Balochistan with budget 14.8 million USD.

iv. Ultra-poor and vulnerable households are given 124,700 productive assets, specifically the out of these 49% females are given these assets.

v. (LACIP) project initiated to improve general living condition of poor households with budget amount 31.56 million Euro in 11 districts of KPK.

vi. Enhancing Food Security through Strategic Interventions in Agriculture this project with budget amount 200 million PKR to enhancing food security in two districts (Sawabi & Thorghar) districts of KPK. vii. Enterprise development under different complimentary projects is implemented to build the capacity of the poor households.

vii. The PPFA has given support to 30,8000 persons with disabilities ix. The PPFA has extended its targeting under the Ehsas and BISP cash transfer programs.

viii. The above-mentioned outcomes are hugely responsible in going ahead to implement poverty reduction agenda and to elevate food insecurity.

Benazir Income Support Program (BISP): the BISP cash transfer is one of the largest social safety net of the Pakistan. The incumbent federal government of Pakistan has launched the BISP cash transfer program in 2008 to cushion the adverse influences of the hike in food prices. The program was initiated to support the extremely poor households to maintain consumption smoothing and women empowerment to build their capacity to stand against covariate shocks. Primarily, the program targets cash transfer to the highly poor and vulnerable women and their families from all over the Pakistan regardless of their racial identity, political affiliations, religious beliefs, and geographic locations. The long-term objectives of the cash transfers are to meet the targets of Sustainable Development Goals (SDGs) on ending the chronic and extreme poverty and women empowerment. Mainly, the BISP cash transfer provides unconditional cash transfers to over 5 million poor households belong to all provinces of the country. Unconditional cash transfers are those which are disbursed to the beneficiaries unconditionally and they can consume it wherever the recipient wants, while conditional transfers are provided on fulfilling some described conditions. The beneficiaries are given cash transfer quarterly to smooth their consumption to meet the dietary needs of the households. Although these conditional social assistances are not covered the wide-scale of the beneficiaries as unconditional cash transfer is covering, but these complimentary programs are also helping to contribute in poverty reduction and ensuring food security.

The other important aspect of the BISP is that it has strong institutional and administrative infrastructure. The program is closely linked with local communities in all over the Pakistan such as tehsil level offices etc. Such institutional inclusiveness makes the BISP beyond a cash transfer program, which is a flagship program to launch social protection programs to target the highly vulnerable communities, specifically in far-flung areas of the Pakistan. In short, the aforementioned reasons make the BISP one of the leading flag-ship social safety net of the country. The key achievements of the BISP are given as follows.

i. The BISP impact assessment reports conducted by the Oxford Policy Management (OPM) have suggested that the BISP cash transfer is found helping the beneficiaries to consumption smoothing.

ii. The independent researchers have found that the BISP is contributing to achieve the food security and nutrition level among the poor households

iii. The researches have revealed that the program is strongly helping to maintain the women empowerment, social and economic empowerment.

iv. The cash transfer is helping to achieve the social and financial inclusion of the marginalized people of the community.

v. The budgetary allocation of the unconditional and conditional cash transfers is increasing over the time.

vi. The BISP has given the census-type household survey called NSER, which have become the central data sets to identify the poor households for other social protection programs.

vii. The researchers also have identified the other socioeconomic influences of the BISP cash transfer on the beneficiaries.

Despite above-given documented success stories of the BISP cash transfer. The critics of the programs are raising their concerns on the probable institutional and financial irregularities perpetrated by the administration at local level. Furthermore, the size of the amount is also criticized that having such amount around PKR 1900 per month is not sufficient to reduce poverty and food insecurity. Some researchers have found the political implications of the BISP cash transfer due to its name. Nonetheless, in spite of the mentioned criticism, the BISP cash transfer is one of the significant social safety nets of the South Asia as well, and its role in achieving the consumption smoothing among the poorest household is unavoidably significant in Pakistan.

Ehsas Cash Transfer: The Ehsas cash transfer program under the institutional framework of the BISP was launched by the incumbent federal government on March 27, 2019. As far as the coverage of the Ehsas is concerned, it has become the largest social safety net along with the BISP. Specifically, with the outbreak of the COVID-19, the program has tremendously socially and financially assisted the large scale of the population to appease the acrimoniously adverse impacts the outbreak of the COVID-19.

According to the Government of Pakistan (2021-22), the *Ehsas* program is unique in its design and structure, which has initiated multiple projects aim to reduce poverty, enhancing food security level by emergency cash transfers, reducing the health risks, and initiating the programs to increase the employability of the youth etc. The main instruments which establish the prioritization of the safety net pillars under the Ehsas framework are given as follows.

i. The incumbent government of Pakistan is envisaged to increase the spending on social protection.
ii. The government tends to enhance the scope and coverage of the social protection and cash transfers to reduce the poverty and uplifting the living-standard of the poor and vulnerable segment of the society.
iii. Priorities to reduce the malnutrition among the highly poor households.
iv. Extending the Ehsas programs with other social protection programs like PPAF and Pakistan Bait-ul-Mal.

The above highlighted points are indicating the future of the cash transfers in the Pakistan. The total spending by the federal governments on both BISP and Ehsas programs since their inception is PKR 1,118 billion. And, their joint coverage 14.40 million people during 2019-20, which demonstrates the huge coverage of the cash transfers. The key initiatives under the Ehsas program for food insecurity include: Ehsas Emergency Cash Transfer, Ehsas Nashonama, Ehsas Amdan Program, Ehsas Langar, Ehsas Koi Bhoka Na Soye, Individual Financial Assistance (IFA), and many others. The objective of all the programs working under the umbrella of *Ehsas* program is to uplift the living-standard of the highly poor households by maintaining their food security level.

7.4 Way Forward:

Although the cash transfer programs in Pakistan perform admirably, but also necessary to enhance the framework of the existing programs. There are some recommendable steps for consideration to expand the efficiency of the social safety programs are given bellow.

i. It is necessary to upscale these existing programs by involving the philanthropic people of the society and expand the coverage to the needier people.

ii. The prevailing identification methods are not fully transparent and they are hugely costly as well.

iii. Pakistan has limited fiscal space, and requires to enhance the partnership with NGOs, and other organizations which are executing different social assistance and food insecurity elevation schemes or programs.

iv. The government requires to execute the strong political commitment to engage the private sector to contribute in food insecurity elevation programs to eradicate the food insecurity.

v. To spending over PKR 200 billion annually, the country cannot afford it for longer period, which also a fact that private sector does not have visible monetary incentive, but it the government who needs to jerk the incentives in such a way to get involved private sector by using multiple tools.

vi. The digitization of the disbursement of the amount to the poor must be expanded to ensure the transparency in implementing the transfers, while it further develop the capacity of the society to adopt the modern mode of transaction.

vii. Government should transfer these unconditional transfers to the conditional. The continuity of the transfers would achieve the desired outcomes effectively.

viii. The BISP has very strong and inclusive institutional and administrative infrastructure which is inclusive and closely linked with communities. So, we need to bring all social safety nets under the umbrella of the BISP rather than spending too much on the administrative bodies whether it is run by federal government or private governments.

Chapter 08
Conclusion

This chapter of the underlying study consists of the conclusion of the overall study. Whereas the chapter is providing some conclusive remarks along with policy recommendations on the biases of key findings of this specific study. In this chapter, we try to explain different sections which are: section 8.1 is the concluding remarks of the whole study. On the other hand, in section 8.2 we present limitations of the whole conducted study. In last section 8.3, the study tries to provide some policy recommendations on the biases of results estimation.

8.1 Concluding Remarks:

The impact evaluation of a program plays an important role to estimate the effectiveness of such programs initiated by the government or non-government authorities or by NGOs, s. The quality of impact evaluation helps to reliable effectiveness of the programs, whereas the impact evaluation also depends on different statistical methodologies to assess variations in outcomes attributed to a proper intervention based on cause and effect analysis. To sort out such counterfactuals of the impact evaluation many econometrics designs or techniques are used either experimental or quasi-experimental. The counterfactual analysis can be conducted by identifying the potential control group or non-beneficiary of the project. The average differences between beneficiary and non-beneficiary are termed as Average Treatment Effect (ATE). Such differences are estimated through multiple techniques which are widely implemented by the researchers i.e. Inverse Probability Weighting Regression Adjustment (IPWRA), difference-in-difference (DID), and Regression Discontinuity Design (RDD). The implementation of these techniques depends on the nature of the data and the modality of the programs.

The underlying study will carry two types of significance, one is a contribution to literature and the second will be considered an effective tool for policy formulation. Literature wise we will collect some studies that belong to different methodologies used for impact evaluation of the programs. In which we try to capture the flexibility, strength, and limitation of these different techniques. To consider those limitations a study by Grembi et al, (2016) used an integrated design to integrate difference-in-difference and regression discontinuity design. Which, estimates the evaluation of the program more precisely and accurately. Where the underlying study also aims to compare both Inverse Probability Weighting Regression Adjustment (IPWRA) and Difference-in-Discontinuity (Diff-in-Dis) to check the robustness of the results. To build this analysis the underlying study tries to use the data of BISP cash transfer, which depends on four years of follow-up surveys (2011, 2014, 2014 &2015). Well, the study aims to estimate the impact of BISP cash transfer on food security, further laying on two different indicators Daily kilocalories intake and Food Diversity. Throughout, the underlying study is carrying this path to highlight and interpret the results of two different models and build a precise discussion of the analysis.

The main hypothesis and objectives of the study based on to capture the impact of cash transfer on chronic food security by applying two different models. Where the hypothesis is: does BISP cash transfer is helping to reduce chronic food insecurity among the benefices and which technique is more flexible and robust whether Difference-in-Discontinuity or Inverse Probability Weighting Regression Adjustment (IPWRA). Nonetheless, the specific objectives of our study are outlined as to estimate the impacts of cash, transfer on chronic food insecurity among the households by using Difference-in-Discontinuity, to estimate the impacts of cash, transfer on chronic food insecurity among the households by using Inverse Probability Weighting Regression

Adjustment (IPWRA) and to compare the estimates of both Difference-in-Discontinuity and IPWRA.

The findings of the study are exploring the positive and statically significant impact of the BISP cash transfer on chronic food insecurity. Inverse Probability Weighting Regression Adjustment (IPWRA) estimates are suggesting a strong positive and significant impact of BISP cash transfer on food security outcomes. On the other hand, RD estimation also shows a strong positive and statistically significant impact of BISP on food security outcomes. Hence, the overall results of the underlying study show that cash transfer is helping the poor territory to eradicate chronic food insecurity, and move them upward to purchase quality food. Somehow the comparisons of the results of the different models (TEM) (RDD) and (Diff-in-Disc) show that from the rest of the models the Inverse Probability Weighting Regression Adjustment (IPWRA) is more fixable and compact to estimate the impact evaluation of the program.

8.2 Policy Recommendation:

The findings of underlying study suggest two sorts of policy implication: 1) methodology aspects of impact evaluation of policy intervention, and 2nd) related to cash transfer and household's food security.

i. For impact evaluation IPWRA is the best alternative of RDD to have a comprehensive analysis as the findings of this study has suggested.
ii. Findings of this study suggests that BISP unconditional has positive impact on household's food security, but these impacts are found declining in 2016 (coefficient is almost zero although statistically significant) as compared to base year 2011. So the study

suggests that BISP needs to focus on food related conditional cash transfer or in-kind programs to reduce food insecurity.

8.3 Limitation of the Study:

The underlying research have some limitations which we have failed to incorporate due to time and scope of this research. The specific limitations are outlined as follows.

- Primarily, the ongoing-research have compared quasi-experimental and Inverse Probability Weighting Regression Adjustment (IPWRA) by discussing differences in assumptions and their validity. The discussion shows that IPWRA seems relatively more flexible and easy to implement. However, any statistical test is not implemented to test the assumptions and validity joint-findings such as Monte Carlo simulations and other techniques due to relatively limited scope of the ongoing study. Further study can be conducted by covering up the mentioned limitation which could be more improved.
- We have used household survey datasets conducted by OPM. These survey has problem of attritions such as 10 percent in 2013 &2014 as compared to base year 2011, while 50 percent attrition in 2016 as compared to 2011. Therefore, this dataset is not as suitable to implement difference-in-difference (DID) or difference-in-discontinuity. Therefore, such huge amount of attrition in follow-up 2016 could raise the question on external validity of the techniques related to quasi-experimental techniques.

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