Socioeconomic and Health Impacts Evaluation of Collective Welfare Grids in Pakistan

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Abstract

The study has assessed the welfare impacts of unconditional cash transfers of the Benazir Income Support Programme (BISP) by using impact evaluation panel surveys conducted in 2016 (baseline) and 2019 (follow-up round). The panel survey contains information from both the beneficiary and non-beneficiary households, selected through a proxy means test (PMT) formula. The research has measured the welfare impacts of unconditional cash assistance across and over the time where welfare has been defined by various socioeconomic indicators, including per-adult equivalent monthly consumption, headcount poverty, multidimensional poverty index (MPI) and child deprivation index (CDI). The results indicate that BISP cash assistance has a positive impact on household consumption while conducting the cross-sectional analysis; however, benefiting households are until facing high rates of poverty as the majority of them have not been transited out of poverty. No sustained welfare impact has been found, as the impacts of quarterly cash assistance on MPI and CDI are not significant in our cross-sectional analysis. The panel analysis shows that the recipient households' economic well-being has improved as measured through consumption and child deprivation indices.

Key words: *welfare impact, multidimensional poverty index, proxy means test, poverty, economic well-being, social safety nets*

JEL Classifications: I0, I3, O1

Introduction

Social protection aims to facilitate marginalized and vulnerable segments through public interventions and collective efforts to improve their standard of living and resilience against risks and vulnerabilities , (Bari et al., 2005). Social protection is categorized by six sorts of interventions: social safety nets (SSNs) or social assistance, social security, labor market initiatives, natural disaster management, basic fundamental facilities for the destitute, and adaptation instruments in the form of laws and policies opted to protect females from violence, children from early marriages, and people from exploitation like bonded labor and child labor (Clouston & Link, 2021).

Over time, social protection programs have gained attention by realizing that economic growth alone is insufficient for poverty alleviation—and that has why they have been placed as the third pillar of inclusive growth, besides sustained economic growth and social inclusion (ADB, 2013). The aim is to protect impoverished segments by managing uncertain risks, building their resilience and making societies more equitable. The success rate of SSNs in various countries depends on many factors, including targeting, coverage, enrollment of the beneficiaries and adequacy of financial assistance (World Bank, 2015). SSNs' welfare impacts in reducing poverty are debatable; still, they are gaining popularity as an effective mechanism for poverty reduction in the developing world (Roderer et al., 2022).

The need for and emergence of SSNs in Pakistan is connected to both the demand and supply side factors, where on the demand side, the country has been facing various vulnerabilities, including economic crises, political instability, natural disasters, high inflation and unemployment, growing population and high poverty rates (24.3% for the 2015 year). On the supply side, the country lacks a systematic and comprehensive social protection framework to mitigate all forms of vulnerabilities. Although Zakat and Pakistan Bait-Ul-Mal emerged in the 80s and 90s, followed by micro-finance initiatives in the 2000s, until the nature and targeting of social safety net programmes do not intend to eradicate poverty on a sustainable basis, as the majority of the interventions were designed for smoothing consumption (Jahan et al., 2019).

After establishing the poverty reduction strategy paper (PRSP) in 2001, the Social Protection Policy (NSPP) was prepared in 2007, and this laid the foundation for the Benazir Income Support Programme (BISP) in 2008. The program is recognized among the top programmes in the world in targeting and coverage (World Bank, 2015). The programme has provided cash assistance to 5.8 million families (ever-married women) with a quarterly stipend of Rs. 5000 (around US $35). Besides, the programme aims to assist the children of low-income families in completing their primary-level education. So far, 3.5 million children are enrolled, and their mothers have been receiving an additional top-up of Rs. 750 per quarter for male children and Rs. 1000 per quarter for female

The current issue and full text archive of this journal is available at www.jraspublications.org/index.php/JRAS/issue/archive
Journal of Research in Administrative Sciences (JRAS)
V XII(II), 19-30, ISSN: 2664-2433

children, with the condition that the child will attend school and meet a minimum attendance goal of 70 percent (2021).

A number of studies have been carried out to estimate BISP cash transfer's welfare impacts, but these studies have lacked robust impact evaluation data, especially the longitudinal survey. Most of the studies are qualitative in nature and have been conducted on limited sampled observations [12,16,17,20]. The studies by (Nayab & Farooq, 2014) and (Zoneira et al., 2018) measured BISP's impact on poverty, but the analysis is cross-sectional in nature and lacks trend analysis. The technique of measuring the impact has also remained an issue in earlier studies, as none of the studies has used robust evaluation techniques, i.e., Regression Discontinuity Design (RDD)and difference-in-difference (DiD) approaches.

The proposed research has attempted to develop various indices, i.e. the child deprivation index and the multidimensional poverty index, to measure the welfare impacts. These impact areas are developed by considering the potential theory of change in BISP, where the programme aims to improve consumption in the short run and poverty eradication in the long run. Therefore, one can expect significant impacts on consumption, headcount poverty, child deprivation, and multidimensional poverty indexes (Walker et al., 2016).

The analysis is carried out using both the cross-sectional and panel survey, where the baseline was conducted in 2011, followed by an impact evaluation survey in 2016. The study will contribute both to academia and from a policy point of view. On the academic side, it will update the impact evaluation literature by conducting a robust statistical panel analysis where none of the studies have earlier explored the impacts on the child deprivation index and the multidimensional poverty index. Regarding the policy perspective, the analysis will help to re-think the role of social safety nets in poverty eradication in Pakistan. The analysis will also help policymakers understand how social safety nets can be used in promoting sustainable development and achieving SDG indicators (Eiswerth et al., 2020).

The rest of the study is organized as follows. Section 2 summarizes the review of various studies pertinent to the welfare impacts of safety nets. Section 3 explains the social safety net initiatives in Pakistan, including BISP. Section 4 encompasses the data description and the methodology employed. Section 5 comprises the results of the study and the last section pertains to the conclusion and policy implications.

Review of the Literature

In developing countries like Pakistan, SSNs are broadly considered protective mechanisms for helping the vulnerable and deprived and enhancing inclusive growth (Barrientos & Hulme, 2008). Social safety nets are widely debated regarding their impacts on socioeconomic indicators, ensuring livelihood, relieving deprivation, improving purchasing power and ensuring food security. Besides, safety nets have been used as a pragmatic mechanism for helping the poor graduate from poverty. There is a plethora of studies available that exclusively deals with the welfare impacts of safety nets on different economic indicators. The present section has reviewed the theoretical and welfare impacts of social safety nets.

Welfare Impacts of Safety Nets

As detailed earlier, social protection and labor (SPL) interventions comprise social safety nets (SSN), social insurance and labor market programs. They may differ on objectives; however, the aim is to promote resilience, equity and opportunity. SSN programmes are non-contributory interventions that target the poor and vulnerable through unconditional and conditional transfers. Social insurance interventions work through contributions to help individuals against various vulnerabilities, including aging, sickness, and natural disaster. Labor market programs can be contributory or non-contributory with the aim to protect individuals from unemployment and loss of income (World Bank, 2018).

With time, developing countries have been diverting more resources to SSN programmes, averaging 1.5 percent of their GDP. The amount varies across regions; the percentage is 2.2 for Europe and Central Asia, 1.5 for Africa and Latin America, 1.1 for East Asia, 1 for the Middle East and East Asia and 0.9 percent for South Asia. The donor-funded SSN programmes are mostly operational in fragile and conflicted countries with little financing from the government, i.e. Ethiopia, Somalia, and South Sudan. The type of programme also varies across regions. For example, South Asian countries heavily rely on unconditional cash transfers and very little is spent on conditional cash transfers (5%) and fee waiver programmes (4%). The Latin American countries allocate a 21 percent share to CCT interventions and only 0.13 percent to UCT-related programmes (Aspire Database, 2017). The lowest coverage given population and the bottom quintile is in South Asia and the highest in Europe, reflecting that European countries are allocating more resources to SSNs. In low-income countries, 18 percent of coverage comes from SSNs, and 2 percent each comes from social insurance and labor market interventions, thus totaling 22 percent. Still, UCT is the most popular intervention in developing countries, including South Asian countries (Fishback, 2022).

The welfare impacts, mostly captured through household surveys, vary across the countries. In the poorest quintile, they contributed to reducing headcount poverty by 8 percent and the poverty gap by 16 percent. The impacts are fewer in low-income countries compared to high-income countries (2% reduction in poverty compared to 15%). The degree of impact depends on the coverage, targeting type and transfer amount. Georgia and South Africa have the highest poverty reduction impacts with 42.6 percent and 40 percent, respectively, whereas Chad has only a 0.1 percent impact and many others have no impact. Empirical evidence suggests that cash transfers generate multiplier effects at the household level (Daidone et al., 2016) and spillover effects in local communities (Thome et al., 2016). Evaluating seven African countries shows positive impacts on crop production and household consumption (Daidone et al., 2016), and an increase in consumption value was found to total more than the transfer amount itself in Zambia. They also led to changes in the pattern of crops in Ethiopia, Malawi, and Zimbabwe (Thome et al., 2016). The meta-analysis of seven African countries shows that household consumption, on average, increased by $0.74 for each $1 in the transferred amount (Ralston et al., 2017). Cash transfer programmes improve household resource diversification and, thus, also allow benefiting households to manage the risks effectively (Barca et al., 2015). They also improve savings, as Ghana and Zambia found improvement in savings by 11 and 24 percent, respectively (Daidone et al., 2016). Though spillover effects are difficult to measure, the study by (Thome et al., 2016) found that the impacts were diffused over a population greater than the beneficiary population.

Regarding national impacts, (Zoneira et al., 2018) estimated the welfare impact of BISP and Zakat on headcount poverty, MPI, child school enrollment and women's empowerment using the Household Integrated Economic Survey's (HIES) 2013-14 data. The results indicated that the BISP cash assistance had a positive impact in reducing headcount poverty by 4 to 7 percentage points. (Hassan & Bibi, 2016) attempted to measure the role of BISP cash assistance in achieving food security by using primary data for Barikot, district Swat, KPK. Positive impacts were found on certain food items, i.e., wheat, sugar, milk and vegetable consumption.

(Nayab & Farooq, 2014) estimated the welfare impact of BISP's cash assistance by using the Pakistan Panel Household Survey, 2010 (PPHS) and found that the recipient group is in the most disadvantaged position as compared to those who had never attempted to apply for benefits and the group that had attempted to apply but had not received them. The study found positive impacts on each household's health and food expenditures, but no impact was found on women's empowerment, child schooling and poverty. The BISP impact evaluation was conducted by Oxford Policy Management (OPM) in three consecutive years: 2013, 2014 and 2016. The study found that cash assistance positively impacted poverty measured through Food and Energy Intake (FEI) and women's empowerment as measured through women's mobility and control over cash.

(Naqvi et al., 2014) the BISP cash assistance's impact on poverty was estimated using primary data in Mankera district, Bhakkar, Punjab. The results have shown that cash assistance has positive

Journal of Research in Administrative Sciences
Volume XII, Issue II, 2023, 19 -30

impacts on food consumption. Similarly, (Malik et al., 2013) found that BISP cash assistance has positive impacts on poverty reduction by using primary data for the Peshawar district. Shahzad (2011) explored the impacts of BISP cash assistance on women's empowerment using primary data in four cities (Multan, Mianwal, Sanghar and Mirpurkhas) and found a positive impact on household food consumption. (Gazdar & Mallah, 2010) pointed out that beneficiaries of BISP were still poor due to a lack of political association with the opponents' parties.

Social Safety Net Initiatives in Pakistan

Pakistan falls among those few developing countries whose constitution delineates social security as the civil right of every citizen. Article 38 of the Constitution indicates that the state is responsible for providing social security and other basic needs, including housing, clothing, food, medical relief and education, irrespective of caste or race, creed and sex. Pakistan has remained prone to a series of challenges, i.e., economic crises, political instability, and natural calamities, i.e., floods, pest attacks and earthquakes. To cope with socioeconomic problems, various governments, from time to time, have initiated many programmes to protect the needy and poor populations. The history of social safety nets and social protection in Pakistan has emerged specifically from the private and public sectors. Public sector schemes have been implemented in past decades but have not been persuasive in the social protection framework. Most of the schemes, such as the Rural Works Programme, Village Aid, People's Works Programmes, and education and health related services programmes, remained focused on reducing poverty in the past. Public sector schemes can be categorized into two main parts: social safety net initiatives and social security programmes. The first target is impoverished and vulnerable poor communities. The programmes include PBM, Zakat, BISP, Food Support programme and other safety nets run by federal and provincial governments, respectively. The second category targets formal labor force employees and retirees by providing benefits pertinent to maternity, invalidity, sickness benefits, work-related injuries and old age benefits (Qasim Zafar, Dr. Mhammad Shabbir, Dr. Sadaf Mahmood, 2021). The schemes include Employees Old Age Benefits Schems (EOBI) and Workers Welfare Funds (WWF) .

Historically, SSNs in Pakistan remained limited to private transfers and the zakat system. The zakat system commenced in the 1980s under the Ordinance of Zakat and Usher, while Pakistan Bait-ul-Mal (PBM) was established in 1991 as a sovereign body. The amount of assistance provided to people experiencing poverty under these systems was very limited and little, along with little coverage of poor, irregular modes of payments. However, Zakat was offered bi-annually, while PBM payment was offered annually to the poor. The broad need for SSNs in Pakistan specifically emerged after the 2005 earthquake, high inflation in the late 2000s and floods in 2010. Subsequently, the government designed and opted for the National Social Protection Strategy (NSPS) in 2007 to address and meet the basic needs of the poor and deprived. Now, various formal and informal sector programmes are being implemented by the governments to cater to the needs of underprivileged segments. The detailed descriptions of all safety net programmes do not come under the scope of this paper. However, functions of safety net initiatives operating at present in the country are tabulated and placed in Appendix A.

Whether or not these programmes have had incredible impacts on target beneficiaries is still debatable in the literature. Still, the country is transitioning to improve SSNs as the programmes have faced operational and financial constraints and operational challenges of targeting, coverage and efficient service delivery (World Bank, 2015). Such initiatives need not only to improve accessibility to the impoverished but also help the poor to take them out of poverty and to escalate their social security. Other challenges/issues include overlapping problems, duplications, lack of coordination between different organizations and fragmentations, which needs greater attention to be tackled properly for the greater impact of these programmes (Nayab & Farooq, 2014).

BISP's Performances and Achievements

Poverty in Pakistan is dynamic in nature as a large population is found around the poverty line and any micro and macro shock is likely to affect them (Arif & Farooq, 2014). Keeping in view poor economic growth and high inflation, the Government of Pakistan launched BISP as a flagship programme in July 2008 to smoothen consumption of poor and vulnerable households. Its long-term impacts include the eradication of poverty and the promotion of women's empowerment. Initially, the beneficiaries were selected by parliamentarians; however, BISP followed a scientific targeting mechanism in 2009 by selecting beneficiaries through the Proxy Means Test (PMT) formula. HIES 2008/09 was used to select socio-demographic and economic indicators that were easily verifiable and had optimal per capita household consumption predictions. The PMT formula determined the welfare status of the household on a scale between 0-100. After the establishment of the formula, a door-to-door survey was conducted in 2010/11 throughout the country by covering 27 million households with 87 percent coverage of the total population. A threshold score of 16.17 was established to identify eligible beneficiaries. There could be multiple eligible families within the eligible household. Crucially, within each eligible family, a Receiver Woman was identified, defined as every ever-married woman with a valid Computerized National Identity Card (CNIC) eligible to receive the cash benefit. Around 5.8 million beneficiaries have received quarterly unconditional cash assistance until June 2019 (GoP, 2018). BISP is also among the world's pioneers in disbursing payments through the biometric verification system (BVS) as all the beneficiaries have received payment after live thumb/finger verification from NADRA. Despite political regime changes, the programme expanded over time with its budgetary allocation of PKR 34 billion in 2008/09 to PKR 180 billion in 2019/20.

Data and Methodology

The current section has explained the data used and the methodology employed by the study.

Data Description

To investigate the impact of BISP's unconditional cash assistance on selected welfare indicators, we have used BISP's Impact Evaluation Panel Survey conducted by Oxford Policy Management (OPM). The panel survey was designed to gauge BISP cash assistance's impacts on various indicators, including per adult equivalent monthly consumption, headcount poverty, multidimensional poverty index (MPI), nutrition, livelihood, assets, saving, and women's empowerment. The evaluation survey was typically designed to gauge impacts where a baseline was established in 2016 (right before intervention) by surveying both the beneficiary and non-beneficiary households. After 2 years of intervention, a series of follow-up rounds were conducted in 2013, 2014 and 2016 to gauge the impacts of the intervention. The current research has used only the baseline and the 2019 round, as sufficient time passed after the intervention until 2016; thus, one can expect interventions to have socioeconomic impacts.

The baseline survey was conducted from 8,675 households in all four provinces of Pakistan. Since impact evaluation requires robust treatment and control groups, BISP established treatment and control groups based on narrowed PMT bandwidth; households having a PMT score between 16.17 were declared as beneficiaries and households having scores between 16.18 and 21.17 were declared as non-beneficiary households. Establishing a baseline helped compare the beneficiary (treated) and non-beneficiary (control) households across that time and over time.

The 2019 follow-up round covered 9,159 households (Table 1). However, one can observe a high attrition rate between the rounds (2016 and 2019) due to data matching issues, as the baseline was conducted right before the poverty scorecard survey in some areas. Therefore, households that were found to be matched on PMT scores in both the baseline survey and poverty scorecard survey were considered valid, and the rest were dropped.

Table 1: Sample Size of BISP's Panel Data

Province	Households Surveyed in 2016 (Baseline Survey)			Households Surveyed in 2019 (Evaluation Survey)			Panel Households (2016 and 2019)	
	Rural	**Urban**	**Total**	**Rural**	**Urban**	**Total**	**Target**	**Control**
Punjab	2389	773	3162	2287	999	3286	580	419
Sindh	1524	810	2334	1794	1213	3007	1001	233
KPK	1533	521	2054	1505	670	2175	651	269
Balochistan	829	296	1125	434	237	671	154	73
Total	**6275**	**2400**	**8675**	**6020**	**3119**	**9139**	**2386**	**994**

Source: Estimated from the BISP Impact Evaluation Survey 2016 and 2019

Methodological Framework

To accomplish the objectives of the proposed research on selected welfare indicators, we have conducted both bivariate and multivariate analyses. The selected welfare indicators are per-adult equivalent monthly consumption, headcount poverty, multidimensional poverty index (MPI) and child derivation index (CDI). The reason for selecting impact variables is the potential BISP's impact, where the 'Theory of Change' suggests that BISP's cash transfer will help in consumption smoothening in the short-run and assets building in the long run.

We have used various statistical techniques to gauge over time and across the impacts, i.e. Regression Discontinuity Design (RDD) and difference-in-difference (DiD). However, one of the major drawbacks is to tackle selection biasness in the evaluation as beneficiary (treated) households vary from non-beneficiary (control) households on socio-demographic characteristics. Propensity score matching (PSM) is a potential solution to avoid selection biasness; it provides appropriate comparisons by constructing a treated and valid counterfactual group. However, the technique faces certain challenges, i.e., weak internal validity and an absence of long-range comparisons (Caliendo & Kopeinig, 2008).

In multivariate analysis, we have used the Regression Discontinuity Design (RDD) technique to gauge the cross-sectional impacts for the 2016 round, where beneficiary households were compared to non-beneficiary households on selected welfare indicators. Similarly, we have applied the Difference in Difference (DiD) technique for panel households to measure the welfare impacts over time. As detailed in Table 1, we have data from 3380 panel households who were interviewed in both the 2011 and 2016 rounds. It is worth mentioning that all the beneficiary households cannot be compared with non-beneficiary households due to variations in socio-demographic and economic characteristics. Therefore, we have developed two comparable groups for comparison; beneficiary households with a PMT score from 11.17 to 16.17 were compared with non-beneficiary households with a PMT score from 16.18 to 21.17.

The bi-variate analysis has covered a comparison of socio-demographic and economic characteristics between beneficiary households and non-beneficiary households by developing two bandwidths of the poverty score, wherein households having scores above 11.17 and below 16.17 are declared as beneficiary households while households having scores above 16.17 but below 21.17serve as the non-beneficiary group.

Before explaining the methodology, it is necessary to provide details on the measurement of selected welfare indicators as follows:

1) ***Headcount poverty*** is measured by following an official methodology that uses food and non-food consumption expenditures. The method may be called the cost of basic (CBN) approach, where the poverty line is set to fulfill basic food (2350 caloric intake) and non-food basic needs. Using the 2013 official poverty line (Rs. 3030 per adult equivalent per month), we have used Rs. 2542 poverty line for 2011 and Rs. 3240 for 2016. It is worth mentioning that the Planning Commission has updated the poverty line (Rs. 3030 per adult equivalent per month) under the CBN approach in 2013/14. The same poverty line was deflated for 2011 and inflated for 2016 year by using the Consumer Price Index (CPI).
2) The ***multidimensional poverty index*** (MPI) is constructed by following the Oxford Poverty and Human Development Initiative (OPHI) methodology. The MPI index is calculated by using three dimensions, including education, health and standard of living. Overall, 11 indicators are taken from 3 dimensions. Equal weights are assigned to each of the dimensions by following the OPHI methodology. A household will be considered deprived and an MPI poor if s/he is deprived in 1/3 of the weighted indicators. Details on the definition of indicators are given in Appendix B.
3) The ***child deprivation index*** (CDI) is constructed using the following OPHI methodology. The same is also used by Iqbal & Nawaz (2017) for constructing the health index of Pakistan and by Wasswa (2015) for the child poverty index of Uganda. The index is developed at the household level by selecting more indicators related to children, and equal weights are assigned to five dimensions. A household is considered to be deprived and CDI poor if any household is deprived in 1/3 of the weighted indicators. Details on the definitions of the indicators can be seen in Appendix C.

Regression Discontinuity Design (RDD) Technique

As detailed above, we have employed the Regression Discontinuity Design (RDD) in the 2016 round to gauge impacts on selected welfare indicators. The technique aims to measure the impact of any intervention by comparing the beneficiary households with non-beneficiary households. The RDD is a quasi-experimental technique used in the evaluation of cross-sectional surveys. Here, we have employed the RDD for evaluating the impact of BISP's cash assistance on selected welfare indicators by using various fixed bandwidths, i.e., +/-3 to +/-5, and optimal bandwidth. The reason behind using various bandwidths is to ensure internal validity. In other words, beneficiary and non-beneficiary households' socio-demographic and economic characteristics must be the same, as one can expect a concise comparison while reducing the bandwidth.

The RDD technique encompasses strong internal validity for those households located near or close to the threshold, which gives Local Average Treatment Effects (LATE) for households near the threshold but weak external validity for those farther from the cut-off—that is why we excluded benefiting households having scores below 11.17. Under certain assumptions of RDD, we have used observations close to the cut-off/threshold for assessing the impact of the program on the outcome variable (OV) by taking the difference in the OV of the treatment and control group observations around the cut-off point, as illustrated below:

$$OV(1) - OV(0) = (OV_i|x_i = 1, BISPscore_i) - E(OV_i|x_i = 0, BISPscore_i)$$

The existing available literature has portrayed two types of RDD, namely sharp RD, wherein only eligible households can be selected for assistance while non-eligible households will not be part of the programme, and perfect compliance in selecting beneficiary and non-beneficiary households is possible. In Fuzzy RD, however, some non-beneficiary group households may receive assistance based on some socioeconomic characteristics like disability, and this approach does not require perfect compliance from beneficiary and non-beneficiary households. Here, we have used Fuzzy RD, as the BISP's assistance has also been given to some of those eligible households with a poverty score above 16.17. Furthermore, here we have used a non-parametric approach that involves estimating differences in the intercepts, i.e. discontinuity intwo local polynomial estimators from each side of the eligibility cut-off/threshold. Formally, for positive bandwidth h:

$$\min_{\beta} \sum_{i=1}^{n} \left(OV_i - \sum_{j=0}^{p} \beta \,(BISPscore_i - c_0)^j \right)^2 K\left(\frac{BISPscore_i - c_0}{h}\right)$$

Triangular Kernel weights have been assigned to the observations by using a Kernel Weight approach that we employed to assign higher weights to the observations close to the cut-off point than those observations farther from the threshold.

Difference in Differences (DiD) Technique

The study has employed the difference-in-difference technique to gauge impacts for panel households where the same beneficiary and non-beneficiary households are compared over time (2016 and 2019). The DiD method compares changes in the outcome variables over time between the beneficiary and non-beneficiary groups to estimate the intervention's impact. It evaluates the impact of the program/intervention on the outcome variable 'Y'. Simple DiD results may be misleading, as they do not account for time-invariant characteristics, and all households in both groups are similar. Moreover, household errors are more likely to be correlated to pre- and post-treatment. By looking into this situation, the DiD with each household's fixed effect is more rigorous to use, clusters errors at the household level and avoids serial correlation. We have used the following model for estimating the DiD by using an impact evaluation panel survey of BISP for the 2016 and 2019 rounds:

$$\boldsymbol{Outcome = \beta 0 + \beta 1\, time + \beta 2\, bisp\_assistance + \beta 3\,(time * bisp\_assistance) + fe + \varepsilon}$$

Where the outcome is CPI, MPI, Headcount poverty and Per adult equivalent monthly consumption expenditures, respectively, β0 is the constant term, bisp_assistance 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 2016 and 1 if the time is 2019; time*bisp_assistance is the interaction term, the product of time and bisp_assistance; fe is each household's fixed effect, and ε is the error term. Here, β3 is the coefficient of the DiD. The negative value of β3 shows the negative impact of the BISP cash assistance on welfare indicators, while any positive value of β3 shows the positive impact of BISP cash assistance over time.

Results and Discussions

The present section encompasses the findings of the study, where section 5.1 has covered bi-variate analysis by making a comparison between the beneficiary and non-beneficiary households, whereas section 5.2 has explained multivariate analysis, including the results estimated through the RDD and DiD approaches.

Socio-Demographic and Economic Characteristics

As detailed in the methodology, we have established two groups for comparison: beneficiary households with PMT scores between 11.17 and 16.17 and non-beneficiary households with scores between 16.18 and 21.17. Therefore, the impact evaluation analysis is conducted within a narrowed PMT bandwidth of+/-5 cut-off.

Table 2 displays the findings on socio-demographic characteristics of beneficiary and non-beneficiary households where both the 2016 and 2019 rounds are used. Three results can be drawn from the analysis: first, beneficiary and non-beneficiary households are almost homogenous on various socio-demographic and economic characteristics, except that the former has been receiving cash assistance. Second, both sorts of households have been facing many vulnerabilities, i.e. larger household size, high dependency rates, lower levels of education and malnutrition. Third, during the 2016 and 2019 period, only a few indicators have shown improvement in each household's well-being among both groups, i.e., improvement in child schooling, reduction in dependency and child labor, whereas there is still a high level of malnutrition.

Table 2: Socioeconomic Characteristics by PMT Score within +/-5 bandwidth

Characteristics	2016 Round		2019 Round	
	PMT Score 11.17 to 16.17	PMT Score 16.18 to 21.17	PMT Score 11.17 to 16.17	PMT Score 16.18 to 21.17
Household size (average)	7.6	7.9	7.7	7.2
Age of head (Avg yrs.)	46.3	44.9	47.9	48.3
Female-headed households (%)	6.6	8.4	11.1	13.8
Male adults (No.)	1.8	1.9	2.1	2.0
Female adults (No.)	1.9	1.9	2.2	2.1
Presence of disabled persons (%)	32.8	31.5	22.7	22.2
High-dependency households (%)*	56.8	48.6	37.7	34.1
Education of HH head (avg yrs.)	2.1	2.4	2.4	2.9
Employment status of household head (%)	81.6	76.4	75.2	72.1
Maximum education of household (avg yrs.)	6.7	6.3	7.3	7.9
Child stunting (%)	41.5	41.9	45.4	43.6
Child wasting (%)	21.1	19.5	18.1	18.1
Child underweight (%)	38.1	39.2	34.0	31.3
Child attendance age 5-12 years (%)	57.0	45	70.4	60.4
Child labor age 5-14 years (%)	16.7	14.1	13.4	10.7

*The dependency ratio is the number of dependent members (below 15 or above 64) divided by the number of independents. Low dependency means the ratio is 0-0.05, medium dependency means 0.51-1 and high dependency means >1:
Source: Estimated from the BISP Impact Evaluation Survey 2016 and 2019 rounds

A comparison among beneficiary and non-beneficiary households on dwelling and asset ownership is provided in Table 3, where both the 2016 and 2019 rounds are documented. The findings reveal that both the beneficiary and non-beneficiary households were at their most disadvantaged conditions in 2016 and 2019 due to their poor living conditions, i.e., less access to toilet facilities, challenges in access to safe drinking water, high crowding rates, and low-quality housing (*katcha*). In addition, the majority of them lack reproductive assets, i.e., land and livestock. Profiling both sorts of households (beneficiary and non-beneficiary) illustrates that both groups have exhibited, on average, similar characteristics across time. The socio-demographic and economic characteristics of panel households from 2016-2019 are placed in Appendix D.

Table 3: Asset Characteristics of Households by PMT Score within +/-5 bandwidth

Characteristics	2016 Round		2019 Round	
	PMT Score 11.17 to 16.17	PMT Score 16.18 to 21.17	PMT Score 11.17 to 16.17	PMT Score 16.18 to 21.17
Owning house (%)	77.9	80.7	81.8	84.1
Small animals (%)	41.7	40.3	32.6	29.7
Large animals (%)	31.8	30.2	28.9	27.2
Owning agricultural land (%)	12.4	13.9	12.2	12.5
Floor katcha (%)	72.9	65.3	59.0	53.1
Access to toilet facilities (%)	60.2	66.9	83.1	86.3
Access to safe drinking water (%)	76.8	79.7	82.5	84.1
Persons per room (Average)	5.1	5.5	4.9	4.4
HH faced shocks during the last two years (%)	73.8	68.5	48.4	49.3

Source: Estimated from the BISP Impact Evaluation Survey 2016 and 2019 rounds

In bi-variate analysis, we have also gauged the performance of cash assistance on selected welfare indicators by comparing the cross-sectional and panel-surveyed beneficiary and non-beneficiary households. The consumption expenditures show that during the 2016 to 2019 period, the average real per-adult equivalent monthly expenditures improved, as shown by both the cross-sectional and panel analysis. The improvement is almost uniform on food and non-food consumption and among both the beneficiary and non-beneficiary households. The estimates of headcount poverty have depicted a decreasing trend in both beneficiary and non-beneficiary households when subjected to a cross-sectional and panel data comparison, but both groups remained more vulnerable and impoverished—according to cross-sectional as well as panel data comparisons—in facing high poverty, as illustrated in Table 4.

Table 4: Monthly Real Consumption Expenditures and Headcount Poverty

Characteristics	Cross-sectional households		Panel households	
	PMT Score 11.17 to 16.17	PMT Score 16.18 to 21.17	PMT Score 11.17 to 16.17	PMT Score 16.18 to 21.17
2016 Round				
Real per adult equivalent monthly consumption (in Rs.)	1864	1869	1845	1867
Real per adult equivalent monthly food consumption (in Rs.)	803	791	808	800
Real per adult equivalent monthly non-food consumption (in Rs.)	1061	1078	1037	1067
Headcount poverty (%) based on CBN Approach	87.1	85.3	87.8	84.4
2019 Round				
Real per adult equivalent monthly consumption (in Rs.)	2349	2481	2278	2311
Real per adult equivalent monthly food consumption (in Rs.)	1173	1206	1159	1154
Real per adult equivalent monthly non-food consumption (in Rs.)	1177	1274	1119	1157
Headcount poverty (%) based on CBN Approach	60.0	52.3	63.1	59.8

Source: Estimated from the BISP Impact Evaluation Survey 2016 and 2019 rounds

For analyzing the welfare impacts on the child deprivation index (CDI) and multidimensional poverty index (MPI), we have used 33 percent thresholds in computing the MPI and CDI indices. In other words, "33" means that a household is deprived if it is deprived in 1/3 of the listed indicators. It is worth mentioning that raising the deprivation cut-off will automatically lower the deprivation rates as measured through MPI and CDI. The results in Table 5 reveal lower rates in the child deprivation index among non-beneficiary households compared to beneficiary households, as reflected through both the cross-sectional and panel analyses. The rates

significantly declined over time: among panel households, 35.3 percent of the beneficiary households were deprived, according to the CDI, in 2016; the percentage declined to 23.4 percent in 2019. The declining rates during the 2016 and 2019 periods are higher among beneficiary households than non-beneficiary households.
The trends in the multidimensional poverty index (MPI) are reported in Table 6. The trends are almost the same, where a higher percentage of beneficiary households are deprived than non-beneficiary households in both the 2016 and 2019 rounds. The panel analysis reveals that an almost similar percentage of households (around 10%) among both groups (beneficiary and non-beneficiary) succeeded in moving out of deprivation as measured through the MPI.

Table 5: CDI and MPI(%) among Beneficiary and Non-Beneficiary Households

Welfare Indicators	Cross-Sectional		Panel	
	PMT Score 11.17 to 16.17	PMT Score 16.18 to 21.17	PMT Score 11.17 to 16.17	PMT Score 16.18 to 21.17
2016 Round				
Child Deprivation Index (CDI)	35.8	28.2	35.3	28.3
Multidimensional Poverty Index (MPI)	32.6	27.0	32.1	27.2
2019 Round				
Child Deprivation Index (CDI)	22.0	16.6	23.4	18.3
Multidimensional Poverty Index (MPI)	21.2	16.4	22.5	17.3

Source: Estimated from BISP Impact Evaluation Survey 2011 and 2016 rounds

Multivariate Analysis

This study has used the regression discontinuity design (RDD) to assess cross-sectional welfare impacts on beneficiary households, where the 2016 round is used for the analysis in which beneficiary households are compared with non-beneficiary households to gauge welfare impacts. It is worth mentioning that the 2011 round cannot be used, as it comprises baseline characteristics and households having no intervention. We used the difference-in-difference (DiD) technique for panel analysis, where we analysed the data of 3380 households (both beneficiary and non-beneficiary) interviewed in both the 2011 and 2016 rounds. The technique helps to draw comparisons over time by comparing the same households.

Welfare Impacts through RDD Analysis

The result of the RD estimates on headcount poverty and per-adult equivalent monthly expenditures for cross-sectional households are illustrated in Table 6. The RD estimates on headcount poverty show that all coefficients of headcount poverty are negative and insignificant at +/-5 PMT score bandwidth. It suggests that the programme does not show any impact on reducing poverty while comparing the beneficiary households with the non-beneficiary households. The RD estimates on total per-adult equivalent monthly expenditures show that the programme improved total per-adult equivalent monthly expenditures of the beneficiary households significantly over those of the comparison group during 2016 by Rs. 92 at +/-5 bandwidth followed by Rs. 148 at +/-5 bandwidth and Rs. 134 at optimal bandwidth.

Table 6: RDD Impact on Headcount Poverty and MonthlyConsumption

2016 cross-sectional Sample	Headcount poverty (CBN)	Per-AdultEquivalent Consumption (Rs.)	Per-Adult Equivalent Food Consumption (Rs.)	Per-Adult Equivalent Non-Food Consumption (Rs.)
+/-5 PMT Score Bandwidth				
RD Estimates	-0.04	92	25.2	66.7
Standard Error	(0.02)	(54.9)	(28.5)	(35.5)
P-value	0.11	0.09***	0.38	0.06***
Sample size left of the cut-off	3683	3683	3683	3683
Sample size right of the cut-off	4173	4173	4173	4173
+/-3 PMT Score Bandwidth				
RD Estimates	-0.06	148	43	105
Standard Error	(0.03)	(68.2)	(35.6)	(43.7)
P-value	0.05**	0.03**	0.23	0.02**
Sample size left of the cut-off	2500	2500	2500	2500
Sample size right of the cut-off	2489	2489	2489	2489
Optimal Bandwidth				
RD Estimates	-0.06	134	37.4	92
Standard Error	(0.03)	(81.3)	(37.9)	(52.5)
P-value	0.07***	0.10***	0.32	0.08***
Sample size left of the cut-off	3277	2662	3158	2467
Sample size right of the cut-off	1490	1278	1721	1159
Bandwidth below the cut-off	3.9	3.1	3.7	2.9
Bandwidth above the cut-off	2.0	1.8	2.2	1.7

* significance at 1 percent, ** significance at 5%, *** significance at 10%
Note: Fuzzy RD estimates are used and the p-value is associated with the robust local polynomial that is bias-corrected, whilst the estimates are based on the kernel triangular method. The BISP poverty score was normalized so that eligibility threshold = 0
Source: Estimated from the BISP Impact Evaluation Survey, 2016 round

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The RD estimates on per-adult equivalent monthly food expenditures show that the majority of the coefficients are positive but have no impact for the 2016 round. However, the RD estimates pertinent to non-food expenditures indicate improvement in total per-adult equivalent non-food expenditures by Rs. 66.7 at +/-5 bandwidth, followed by Rs. 105 at +/-3 bandwidth and Rs. 92 at optimal bandwidth, respectively. The BISP cash assistance's positive impacts on non-food expenditures have led to a positive impact on total consumption expenditures. The visual evidence of the RD estimates pertinent to headcount poverty and total per-adult equivalent monthly expenditures are illustrated in Appendix E.

The RD estimates, as indicated in Table 7, show the welfare impact of BISP cash assistance on two indices, MPI and CDI. The RD estimates show that the majority of the coefficients are negative but insignificant at fixed and optimal bandwidths. This indicates that BISP cash assistance has exerted no impact in reducing MPI and CDI in 2016 for beneficiary households while comparing them with non-beneficiary households having similar characteristics. The visual evidence of the RD estimate is placed in Appendix E.

Table 7: RDD Impact on MPI and CDI, 2019

2016 Cross-Sectional Sample	Multidimensional Poverty Index (MPI)	Child Deprivation Index (CDI)
+/-5 PMT Score Bandwidth		
RD estimates	0.001	0.002
Standard Error	(0.01)	(0.01)
P-value	0.90	0.88
Sample size left of the cut-off	3683	3683
Sample size right of the cut-off	4173	4173
+/-5 PMT Score Bandwidth		
RD estimates	-0.02	-0.005
Standard error	(0.01)	(0.01)
P-value	0.27	0.71
Sample size left of the cut-off	2500	2500
Sample size right of the cut-off	2489	2489
Optimal Bandwidth		
RD estimates	-0.03	-0.005
Standard error	(0.02)	(0.02)
P-value	0.19	0.77
Sample size left of the cut-off	1913	2158
Sample size right of the cut-off	1019	1772
Bandwidth below the cut-off	2.2	2.4
Bandwidth above the cut-off	1.4	2.3

* significance at 1 percent, ** significance at 5%, *** significance at 10%

Note: Fuzzy RD estimates are used and the p-value is associated with the robust local polynomial that is bias-corrected, whilst the estimates are based on the kernel triangular method. The BISP poverty score was normalized so that eligibility threshold = 0

Source: Estimated from the BISP Impact Evaluation Survey, 2016 round

Welfare Impact through DiD Analysis

We estimated the welfare impact of BISP cash assistance by employing difference-in-difference (DID) and using two rounds of panel data, the baseline in 2011 and a follow-up in 2016. The results of the DiD model are reported in Table 8, which shows that per-adult equivalent monthly expenditures remained insignificant over time and DiD observed no impact on per-adult food and non-food expenditures. The impact on headcount poverty is also insignificant. There is a positive impact on the child deprivation index (CDI), as deprivation was reduced by 3.3 percentage points. The impact on MPI is insignificant. Using various cut-offs of CDI and MPI other than 1/3, i.e. 40 percent and 50 percent, the impact is significant at 40 percent and 50 percent (Appendix F).

Table 8: DiD Impact on Selected Welfare Indicators with Normed Poverty Score

Welfare Indicators	Control		Treatment		Difference-in-difference Coef (SE)
	Baseline Mean (SE)	Difference Coef. (SE)	Baseline Mean (SE)	Difference Coef. (SE)	
Per-adult equivalent monthly consumption	1866.7 (43.64)	444.53* (49.76)	1760 (31.57)	439.8* (35.16)	-4.74 (63.25)
Per-adult equivalent monthly food consumption	800 (10.8)	354.1* (16.7)	791.3 (13.20)	94.1* (6.9)	-8.4 (10.9)
Per-adult equivalent monthly non-food consumption	1067 (40.8)	90.4** (43.8)	969 (30.1)	-620.48* (31.6)	3.6 (56.6)
Headcount Poverty	0.80 (0.01)	-0.28* (0.02)	0.85 (0.01)	-0.25* (0.01)	0.02 (0.02)
Child Deprivation Index (CDI)	0.28 (0.01)	-0.10* (0.01)	0.41 (0.01)	-0.13 (0.01)	-0.03* (0.01)
Multidimensional Poverty Index (MPI)	0.27 (0.01)	-0.10* (0.01)	0.37 (0.01)	-0.10* (0.01)	0.0 (0.01)

* significance at 1 percent, ** significance at 5%, *** significance at 10%

Note: The BISP poverty score was normalized so that eligibility threshold = 0

Source: Estimated from the BISP Impact Evaluation Survey, 2011-2016 rounds

Conclusion and Policy Implications

The present research has explored the welfare impact of BISP cash assistance by conducting both cross-sectional and panel analyses. The bi-variate analysis shows that beneficiary and non-beneficiary households have similar socio-demographic and economic characteristics. The findings reveal that BISP has a mild welfare impact, as cross-sectional analyses have shown positive impacts on non-food consumption, total consumption and poverty, whereas there is no impact on the child deprivation index and multidimensional poverty index. The panel analysis shows positive impacts on consumption and the child deprivation index.

The findings draw various implications. First, unconditional cash assistance alone may not help graduate people out of poverty sustainably. The BISP has to focus on conditional cash transfers that would help in asset creation and skill development, i.e., Mexico, Brazil, and Chile have been doing. Second, the current cash assistance (Rs. 5000 quarterly) is insufficient even in consumption smoothening. The amount must be increased to the extent that may help achieve optimal consumption uniformity. Third, the programme should focus on other chronic challenges, i.e., malnutrition, financial literacy, and child schooling, that may help improve SDG goals. Fourth, the control group (non-beneficiary households) suggests that various deserving households are overlooked by the programme. Keeping in view the dynamic nature of poverty, the process of including and excluding deserving households must also be dynamic in nature. Lastly, after the 18th Amendment, social security and safety nets are now provincial subjects. Keeping in view, a social protection framework is required to clarify roles and responsibilities of federal and provincial governments as well as to tap the private sector.

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Appendixes

Appendix A: Multidimensional Poverty Index (MPI), Dimensions, Indicators and Weights

Dimension	Indicator	Definition	Weight
Health	Household nutrition	Household is deprived if have access to only two food items during last 7 days (wheat, wheat flour and rice/rice floor)	1/9
	Child nutrition	Household is deprived if child age 0-59 months old is malnourished	1/9
	Child vaccinations	Household is deprived if any child aged 20-59 months is not vaccinated for DPT or measles	1/9

Appendix C: Child Deprivation Index (CDI), Dimensions, Indicators and Weights

Dimension	Indicator	Definition	Weight
Education deprivation	Child Enrollment (5-14 Years Old)	Household is deprived if any child of age 5-14 years does not go to school	1/5
Labor deprivation	Child labor (5-14Years Old)	Household is deprived if(a) any child in age group 5-11 years old did one hour of economic activity or 28 hours of domestic work during the last week (b) any child of 12-14 years old did 14 hours of economic activity or 42 hours of domestic & economic activities combined is deprived. UNICEF	1/5
Health deprivation	Consult Doctors during sickness	Deprived if household did not consult doctor for a child who is suffering from diarrhea and distance to clinic is more than 30 minutes	1/15
	Child Immunization for BCG, DPT, Polio, Measles, Hepatitis Months Old)	Deprived if any child between age group 0-59 months old is not fully vaccinated	1/15
	Child Stunting	Deprived if any child is stunted/malnourished as per WHO standards	1/15
Food deprivation	Access to quality food	The child is deprived if household do not have access to one of the quality food items like fruits, meat, beef, poultry, fish, milk	1/10
	Access to sufficient food	Deprived if household do not have access to sufficient food during last 12 months	1/10
Housing deprivation	Child crowding	Deprived if household's occupied two or less than two rooms	1/15
	Water	Deprived if drinking water does not meet the MDGs criteria and distance to reach for water is more than 15 minutes	1/15
	Toilet	Deprived if household lack toilet facility at home	1/15

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Appendix D: Socio-Demographic and Economic Characteristics of Panel Households by Poverty Score within +/-5 bandwidth

Characteristics	2016 Round		2019 Round	
	11.17 to 16.17	>16.17 to <21.17	11.17 to 16.17	>16.17 to <21.17
Household size (average)	7.9	7.6	7.9	7.4
Age of head	45.0	46.3	48.1	49.0
Female headed households (%)	6.2	8.1	8.3	9.7
Male adults (No.)	1.8	1.9	2.2	2.1
Female adults (No.)	1.8	1.9	2.2	2.2
Presence of disabled (%)	31.8	33.2	22.9	20.4
High dependency Households (%) *	56.1	48.5	34.5	30.4
Education of HH Head (avg yrs.)	2.9	3.2	2.8	3.1
Employment status of households head (%)	80.8	75.2	74.8	72.6
Maximum Education of Households (avg yrs.)	6.3	6.7	7.1	7.7
Child stunting (%)	40.6	41.5	46.8	46.2
Child wasting (%)	20.2	17.8	16.0	19.0
Child underweight (%)	36.5	37.8	32.9	34.9
Child attendance of age 5-12 years (%)	53.8	43.4	58.8	68.9
Child labor of age 5-14 Years (%)	16.3	14.2	15.2	11.6
Dwelling and Asset Characteristics of Panel Households by Poverty Score				
Owning house (%)	79.0	82.6	83.3	86.5
Small animals (%)	42.7	41.1	36.1	34.9
Large animals (%)	31.3	33	33.0	33.2
Own agricultural land (%)	12.9	15.3	13.0	12.9
Floor kacha (%)	72.9	67.4	64.3	61.5
Access to toilet facility (%)	60.7	65.7	80.9	83.7
Access to safe drinking water (%)	79.7	76.6	81.4	84.7
Persons per room (Average)	5.5	5.1	5.0	4.9
HH faced shocks during last two years (%)	74.2	68.4	49.6	51.2
N	**1210**	**994**	**1210**	**994**

Source: Estimated from the BISP Impact Evaluation Panel Survey 2011-2016

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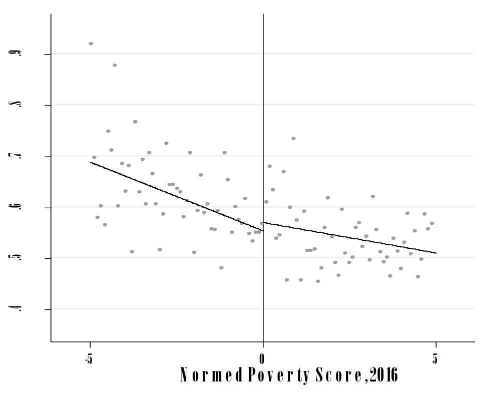
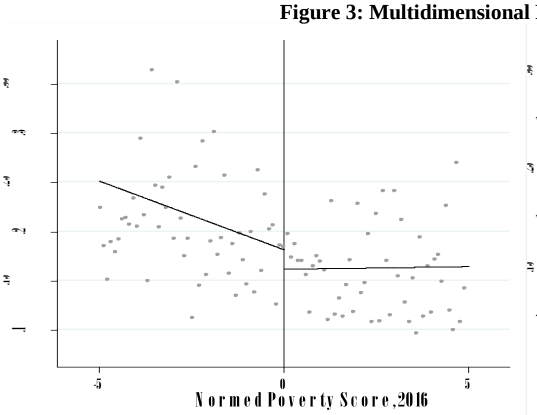
Appendix E: Visual Evidence of RDD Test on Welfare Indicators

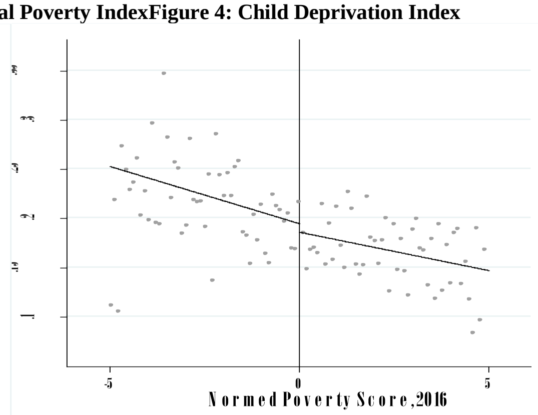
Figure 1: Headcount Poverty **Figure 2: Per Adult Equivalent Total Consumption Expenditures**



Source: Estimated from the BISP Impact Evaluation Survey2016 by authors. Graphs depicts scatter plot of average per adult equivalent monthly consumption expenditures and headcount poverty of each estimation sample with normed poverty score limited to +/-5 bandwidth in 2016 round. A linear regression line with triangular kernel is fit on either side of eligibility cut-off.

Figure 3: Multidimensional Poverty IndexFigure 4: Child Deprivation Index





Source: Estimated from the BISP Impact Evaluation Survey2016 by authors. Graphs depicts scatter plot of MPI and CDI in each estimation sample with normed poverty score limited to +/-5 bandwidth in 2016 round. A linear regression line with triangular kernel is fit on either side of eligibility cut-off.

Appendix F: DiD Impact on MPI and CDI with normed poverty score

Welfare Indicators	**Control**		**Treatment**		Difference-in-difference Coef (SE)
	Baseline Mean (SE)	Difference Coef (SE)	Baseline Mean (SE)	Difference Coef (SE)	
Child Deprivation Index (CDI) at Various Cut-offs (%)					
40	0.23 (0.01)	-0.09* (0.01)	0.37 (0.01)	-0.14* (0.01)	-0.05* (0.01)
50	0.15 (0.01)	-0.06* (0.01)	0.29 (0.01)	-0.14* (0.01)	-0.07* (0.01)
Multidimensional Poverty Index (MPI) at Various Cut-offs (%)					
40	0.18 (0.01)	-0.07* (0.01)	0.30 (0.01)	-0.09* (0.01)	-0.02*** (0.01)
50	0.14 (0.01)	-0.05* (0.01)	0.25 (0.01)	-0.08* (0.01)	-0.03*** (0.01)

* shows significance at 1 percent, ** shows significance at 5%, *** shows significance at 10%. *Note:* The BISP poverty score was normalized so that eligibility threshold = 0

Source: Estimated from the BISP Impact Evaluation Survey, 2011 and 2016 rounds