UNIVERSITY OF WAIKATO

Hamilton
New Zealand

Does the impact of cash transfers differ across poverty measures? Evidence from Pakistan

Zaira Najam and Susan Olivia

Working Paper in Economics 9/21

September 2021

Corresponding Author

Zaira Najam
School of Accounting, Finance and Economics
University of Waikato
Private Bag 3105
Hamilton, 3240
New Zealand
Email: zaira.najam@gmail.com

Susan Olivia
School of Accounting, Finance and Economics
University of Waikato
Private Bag 3105
Hamilton, 3240
New Zealand
Email: susan.olivia@waikato.ac.nz

Abstract

Cash transfers have been increasingly used in developing countries as key elements of social protection and poverty reduction strategies. Pakistan is no exception. In 2008, Pakistan introduced the Benazir Income Support Program (BISP) as an unconditional cash transfer targeted at the poorest of the poor. In this paper, we use five poverty measures, calculated biennially from 2008 to 2014 for 100 districts in Pakistan to assess the effectiveness of the BISP in alleviating poverty. We also examine whether the impact of the cash transfer programs on poverty is sensitive to the choice of poverty measure. Our results show that BISP is associated with poverty reduction using either the conventional money-metric poverty measures or multidimensional poverty measures, however the impact is much larger for the conventional poverty measures, which are distributionally insensitive. The implication is that public policy analysts should be cautious in the conclusions they draw from poverty estimate when evaluating welfare programs.

Keywords

poverty

cash transfers

multidimensional

social protection

Pakistan

JEL Classification

I32

I38

Acknowledgements

We are grateful to the Pakistan Ministry of Planning, Development and Reforms, Benazir Income Support Programme office for their assistance and to John Gibson for his valuable suggestions.

1. Introduction

The experience of countries that succeeded in reducing poverty significantly indicates the importance of sustained high economic growth in achieving this result. However, Ravallion (2001) and Fosu (2011) pointed out that high growth alone is not sufficient for poverty alleviation as the very poor are unlikely to benefit from any trickle-down effect that may result from growth. The challenge for policy makers is thus to combine growth-enhancing policies with the right poverty alleviation policies to create opportunities for the poor so that they can contribute to and benefit from growth (Ravallion, 2004). Consequently, in countries where growth is inadequate or is not pro-poor, there is a need to have well-functioning social safety nets to dissipate the increasing income inequality resulting after the spur in growth (Lee and Park, 2002).

There is growing evidence which shows that social safety net programs play a crucial role in reducing poverty and food insecurity. For instance, Devereux (2002) found that the inclusion of cash transfers in social safety net program in Namibia, Mozambique and Zambia reduce chronic poverty. A study by Acasto and Velarde (2015) show that Phillipines' cash transfer program, the *Pantawid Pamilyang Pilipino Progam* (4Ps) has led to a reduction in food poverty and total poverty among beneficiaries by about 7 percentage points. In India, social safety nets also have a significant impact in improving food security (Pritchard et al., 2013). Using data from 142 countries, the World Bank (2018) *State of the Social Safety Nets* report showed that social protection programs cover 56 percent of the poorest population globally and about 36 percent of the very poor who received safety net benefits escaped extreme poverty because of social safety nets. Data from the report also show that safety nets which include unconditional and conditional cash transfers, food and in-kind transfers, public works, school feeding programmes and fee waivers targeted to poor and vulnerable households also lower inequality and reduce the poverty gap by 45 percent.

Safety nets program not only contribute to poverty reduction, but also allow recipients to boost investment in human and physical capital, to smooth consumption and to engage in more risky but productive activities. Numerous impact evaluation studies on conditional cash transfer program *Progresa*[1] in Mexico have shown a substantial improvement in schooling attendance (Schultz, 2004; Attanasio et al., 2011) and other benefits including a 20 percent increase in households' monthly savings (Harrison, 2019) and a significant improvement in the health of both children and adults (Gertler and Boyce, 2003). Existing evidence on the impact of unconditional cash transfers to vulnerable households in Africa also suggest positive effects on the education and health outcomes of children in beneficiary households (Haushofer and Shapiro 2016; Kremer et al 2013). In Kenya, a year-long randomised trial of Give Directly found that the programme's unconditional cash transfers raised psychological wellbeing and food security (Haushofer and Shapiro, 2016). Findings from Uganda show that beneficiary households reported higher consumption expenditure and used part of the cash transfers on

[1] Later known as *Oportunidades* and now *Prospera*

health and education related expenditures and investment in productive assets (Merttens et al. 2016).

Despite the wealth of interest from policy makers and researchers, there are a few reasons why the evidence of the impact of social safety nets on poverty and other socio-economic outcomes is insufficient. First, the evidence is for traditional, money-metric poverty measures, such as the headcount index (the share of the population living in households whose consumption or income is below the poverty line) and the poverty gap index (the average proportionate shortfall from the poverty line). Yet many developing countries are switching to multidimensional poverty measures to either supplement or replace the traditional money-metric ones (Alkire et al., 2015). Secondly, existing studies that investigated the living standards enhancing aspect of social safety nets only use one specific indicator such as school enrolment or health status. Empirical work has shown that significant percentages of those who are multidimensionally deprived are not monetary poor and vice versa (Alkire and Jahan, 2018). As such, it is thus crucial to understand the poverty-reduction impact of social protection programs in a multidimensional framework. Furthermore, to date, no studies compare the impact of social programs in multidimensional measures versus in money-metric measures. Other aspects of poverty analysis for Pakistan, such as spatial patterns and temporal changes, appear to be sensitive to using multidimensional versus money-metric poverty measures (Najam, 2020).

In 2008, the government of Pakistan (GoP) launched the Benazir Income Support Program (BISP) to minimize the impact of adverse economic shocks and inflation faced by the poor. The BISP is unique case in social protection for several reasons. First, it is an unconditional transfer. Whereas there is evidence that conditions matter for some outcomes (de Brauw and Hoddinott, 2011), more recent papers that have randomized conditionality find that conditions do not affect impacts on all outcomes (Akresh et al., 2013). Second, the BISP is a nationwide program that has expanded quickly – its coverage has increased from 1.7 million beneficiaries in 2008 to 5.3 million in 2016, and it is expected to reach about 8 million beneficiaries by the end of 2019 (World Bank, 2018). These facts provide an ideal setting to explore whether BISP really target the poor areas. There is also a significant timing issue that is especially relevant in the context of Pakistan. Pakistan has made significant progress in reducing its poverty headcount by nearly 66 percent between 2002 – 2016 during which time its economic performance has been erratic with spurts of high growth periods followed by steep decline, indicating that there is no established relationship between poverty and macroeconomic performance in Pakistan (World Bank, 2016, Afzal et al., 2019). In a recent paper, Najam (2020) reported that while monetary poverty has fallen substantially (from 48.1 percent in 2008, to 13.2 in 2014), improvements in non-monetary social indicators remain sluggish, with the multidimensional poverty index falling from 25.7 in 2008 to 22.1 percent in 2014. Why a mediocre economic growth translated to a significant income poverty reduction but not so much on other social indicators has been puzzling. The apparent disconnect between economic growth and the reduction in poverty leads to the question of what policies have contributed to the decline of poverty in Pakistan. Whether the change in poverty numbers is the result of the cash transfers or the result of economic development initiatives is imperative to the research.

In this paper, we are investigating whether the impact of the BISP unconditional cash transfers program on poverty in Pakistan depends on the type of poverty measure used. We use five poverty measures (two multidimensional and three money-metric and one measure from each of these groups is distributionally sensitive), calculated biennially from 2008 to 2014 for 100 districts in Pakistan. With these multitude of measures, we can assess whether choice of poverty measure matters when assessing the impact of social protection programs. Given that we are using data from ex-post perspective in evaluating the effectiveness of BISP on poverty, we use a quasi-experimental approach and employ the Blinder-Oaxaca decomposition method. To the best of our knowledge, this is the first study that examined the poverty eradicating aspect of social safety nets using both the multidimensional and money metric poverty measures.

The rest of the paper is organised as follows. In section 2, we describe the BISP program and briefly discuss existing studies that look at the impact of BISP in Pakistan. Section 3 provide details on poverty in Pakistan, followed by discussion on data and estimation methodology. Section 5 provides the results and Section 6 concludes the discussion with policy implications.

2. An Overview of the Benazir Income Support Programme (BISP)

Pakistan first developed a Social Protection Strategy in 2007 and announced the BISP as its main social safety net program in 2008. The BISP initially aimed to help the poorest of the poor through unconditional cash transfers. It has three main policy goals which include (i) to eradicate extreme and chronic poverty, (ii) to empower women and (iii) to achieve universal primary education (Afzal et al., 2019).

As the Pakistani economy was characterized by high food price inflation when the BISP began in 2008, with its annual inflation rate hitting 21%, up from 12% the year before, there was urgency to increase the declining purchasing power among the poorest members of society. Consequentially, initial program targeting, took place through parliamentarians, who were each asked to identify 8,000 beneficiary households on a prescribed form, on which names and household income information were collected. Under this system of community-based targeting (CBT) through politicians, the initial rollout led to disbursement to over 2 million eligible families (Cheema et al., 2015)

As a result of concerns over the effectiveness and transparency of parliamentarian targeting, a new national targeting mechanism based on Proxy Means Test (PMT) was developed. Weights for the PMT were developed using the 2007-08 Pakistan Living Standards Measurement Survey (PSLM). The PMT is based on 23 variables, which include socio-economic characteristics such as household size, housing type, access to sanitation, educational status, household assets, agricultural landholding and livestock ownership. The PMT procedure estimates the welfare status of a household on a scale of 0 to 100 helping in identifying the poorest households. For the application of the PMT formula, a nationwide Poverty Scorecard Survey was conducted in 2010 covering around 27 million households in the country. A PMT threshold (cut-off score) of 16.17 was used to determine the eligibility of the household for unconditional cash transfer[2]. Among the surveyed households, over 7 million (around 28 percent) households across Pakistan were eligible for the unconditional cash transfer, in which 5.8 million families were active beneficiaries up until 2018 (Iqbal and Nawaz, 2019). The breakdown of surveyed households and the eligible households by four provinces, namely *Punjab*, *Sindh*, *Kyber Pakhtunkhwa* (KPK) and *Balochistan* along with the three federally administrated territories: *Azad Jammu and Kashmir* (AJK), *Gilgit-Baltistan* (GB), and Federally Administered Tribal Areas (FATA), is presented in Table 1. The Poverty Score Card (PSC) Survey covered at least about 80 percent of the population in each of these provinces and territories. Proportion of eligible beneficiary households was highest in FATA (52.5 percent), followed by *Balochistan* and *Sindh* (40 percent)

Table 1: Area Wise Coverage under Poverty Scorecard Survey, 2010

Province	No. of Districts	Estimated Population (in million)	Population Surveyed (in million)	Population Surveyed (%)	HHs Surveyed (in million)	Eligible HHs (in million)	Eligible HHs (%)
Punjab	39	94.36	81.18	86.26	14.88	2.79	18.7
Sindh	27	38.92	34.29	88.11	6.60	2.68	40.1
KPK	24	26.93	21.30	79.09	3.64	1.40	38.5
Balochistan	30	7.62	6.05	79.40	1.10	0.45	40.1
AJK	10	3.87	3.54	88.53	0.58	0.12	20.6
GB	7	1.27	1.13	89.44	0.15	0.05	33.0
FATA	7	3.69	3.06	82.95	0.40	0.21	52.5
Total	**144**	**177.94**	**150.55**	**84.61**	**27.35**	**7.70**	**28.15**

Source: Benazir Income Support Programme (n.d.)

Since the inception, BISP's annual disbursement under the unconditional cash transfer programme increased from 15 billion in 2008 to Rs. 116 billion in 2018 (see Table 2). Up until 2012 the beneficiary households received Rs 1,000 (around US $10) per month which increased to Rs. 1,200 in 2013, Rs 1,500 in 2014, Rs 1,567 in 2015 and finally to Rs 1,611 in 2016. The amount paid to the beneficiary is around 20% of the monthly income of a daily-wage worker and around 10% of minimum wage set by the government of an unskilled labourer (Saleem, 2019). In the span of 10 years, the BISP's releases as a percentage of GDP increased from 0.1% to 0.35%.

[2] BISP chose a 16.17 cut off score keeping in view the budget availability and proposed amount of monthly stipend (Cheema et al., 2015)

Table 2: Yearly BISP Releases and Number of Beneficiaries

Fiscal Years	Total Yearly Releases Rs. Billion	Releases as % of Federal Revenues	Releases as % of GDP (MP)	Yearly Beneficiaries (Nos. in Millions)	Project Phases**	Cash Amount Per Month Per Beneficiary (in Pak Rupees)
2008-09	15.32	1.3%	0.10%	1.76	Phase I	1,000
2009-10	39.94	3.0%	0.19%	2.58	Phase I	1,000
2010-11	34.42	2.2%	0.19%	3.10	Phase I	1,000
2011-12	49.53	2.6%	0.25%	3.68	Phase I & II	1,000
2012-13	50.10	2.6%	0.22%	3.75	Phase II	1,000
2013-14	69.62	3.1%	0.28%	4.64	Phase II	1,200
2014-15	91.78	3.5%	0.33%	5.05	Phase II	1,500
2015-16	102.00	3.3%	0.35%	5.21	Phase II	1,567
2016-17	111.50	3.3%	0.35%	5.46	Phase II	1,611
2017-18	107.00	3.0%	0.35%	5.63	Phase II	1,611
2018-19	116.50	3.0%	0.35%	5.78	Phase II	1,611

Source: Economic Survey of Pakistan 2017-18

Note: ** Phase I of the project was the Community-based targeting, through parliamentarians while Phase II was targeting through Poverty Score Card

For any social safety net program to be successful, the issue of targeting is of utmost importance. Targeting must be cost-effective and be useable by policy makers in a way that can be used to generate lists of potential beneficiaries. Moreover, procedures must be put in place to ensure that the selection of beneficiary is objective, transparent and consistent across geographical areas (Grosh et al., 2008). As mentioned earlier, BISP adopted two different targeting methods to reach out to the poorest of the poor in Pakistan. In the initial phase, which lasted from 2008 to 2011, the beneficiaries of the program were selected through parliamentarians and their political leaders at the local level, which is akin to Community-Based Targeting (CBT) with an extra layer of being political. In the second phase of the program, the BSIP has been targeted using a Proxy Means Test (PMT) since 2011. While the move to the PMT targeting is perceived to be better than CBT as it limits the biases and rent-seeking behaviour of local elites and other community members, the PMT targeting has both inclusion and exclusion errors (Kidd and Wylde 2011).

While designing the PMT, the World Bank (2009) carried out simulation exercises and showed that that if the poorest 20% of the population is set as the target group for the BISP, then the leakage rate is expected to be 40% whereas under-coverage rate is expected to be 61%. This implies that 61% of the poor (the poorest 20% of the population) will be excluded from the benefits while 40% of the beneficiaries are non-poor. There are few case studies like Gazdar and Zuberi (2014) and Saleem (2019) which highlighted the exclusion of households which should have been in the eligible household list. This exclusion error along with transition of the targeting methodology in the last 10 years made it important to examine how effective BISP was in reducing poverty over time under its two different targeting phases.

To examine targeting efficiency, we report the percentage of households who are eligible for the BISP, according to the 2010 PSC Survey. This benchmark is then compared to the percentage of poor households according to either the conventional monetary poverty measure or the multidimensional poverty measures (see Table 3). According to the PSC Survey, 28% of households nationally are beneficiaries of BISP, yet the MPI poverty measures suggest that 46 percent of households are poor. Thus, according to this comparison, there is an under-coverage in targeting of about 64%. The gap is even bigger if we use the distributionally sensitive multidimensional poverty measure MDPI developed by Datt (2019), where 89% of households are considered poor. In contrast, when the comparison is made between the PSC eligible households and those who are considered poor under the conventional head count poverty index, there seems to be over-coverage with the BISP as it has a higher share of households who are eligible than are counted as poor with the head count index. This evidence indicates there is a need to investigate how effective BISP is in the presence of these discrepancies in the eligibility of poor households.

Table 3: Percentage of eligible households under the 2010 PSC and poor households using conventional, MPI and MDPI for 2010

Provinces	PSC Eligible Household	Conventional Poverty Measure Poor Households*	MPI Poor Households*	MDPI Poor Households*
Punjab	18.7%	18.9%	40.3%	90.7%
Sindh	40.1%	21.9%	45.7%	80.3%
Balochistan	40.1%	11.8%	78.5%	98.0%
KPK	38.5%	20.7%	57.3%	95.6%
National	**27.9%**	**19.5%**	**45.7%**	**89.3%**

Note: * authors calculation based on Najam (2020)

The impacts of BISP have been studied in several papers, including Pashaet et al. (2018) who observed stability in social status of beneficiaries and increase in their consumption on *Thatta* district of *Sindh* province as a result of BISP. Junaid and Mohsin (2017) in their research on two districts from *Sindh* province showed that a total of 105 out of 263 beneficiaries escaped from poverty after the BISP. Amrin and Ashfaq (2020) in their research on a city in *Punjab* province found that BISP increases beneficiaries' food expenditure. Afzal et al. (2019) in their work showed the positive impact of BISP on headcount index. Azeem et al. (2019) in their extensive study on Pakistan for 2010-11 showed the poverty reducing impacts of social protection programmes. Nayab and Farooq (2014) studied the impact of BISP on food and health expenditures. The detailed evaluation conducted by Oxford Policy Management (OPM) on BISP suggests around 3-7 percent reduction in poverty. This range of reduction depends on the poverty line used (Cheema et al., 2015).

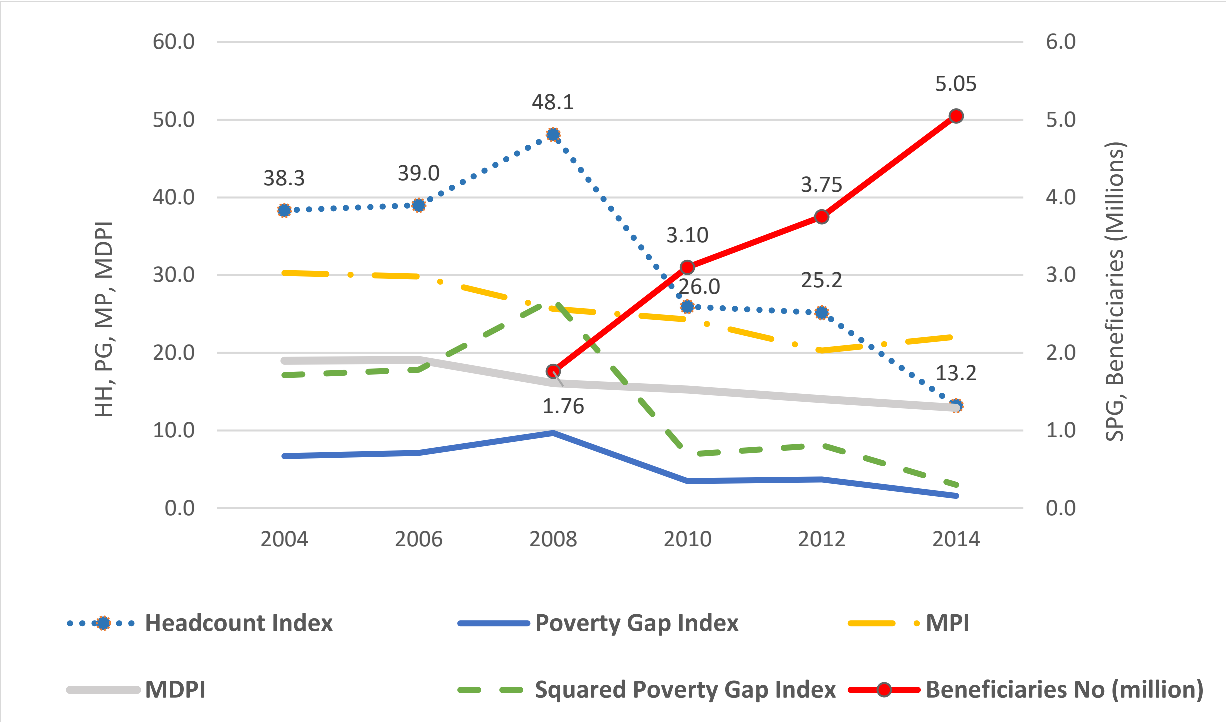
All of the papers mentioned above used money-metric poverty measure to gauge the impact of the BISP. Furthermore, studies that look at the impact of BISP on poverty only concentrated at a rather limited geographical scale. Our paper differs from existing studies in the following way. First, we use poverty estimates for all districts in Pakistan to examine the impact of the BISP. Due to the spatial heterogeneity in terms of economic development between provinces and districts as pointed out in Najam (2020), and thus it is important to look at the effects of the social program at the disaggregated level for Pakistan. Secondly, we use both money metric and multidimensional poverty measures to analyse the contribution of BISP in reducing poverty. BISP beneficiaries have been criticised for spending their money on consumption goods rather than improving their human capital (Junaid and Mohsin 2017). Consequently, analysing the effect of BISP on multidimensional poverty measures can provide some evidence on spending priorities of the beneficiaries.

3. Poverty in Pakistan: Background and Data

Figure 1 illustrates the evolution of average poverty rates over the six waves of surveys from 2004 to 2014. The three money-metric measures shown in the figure are the headcount index (HH), the poverty gap index (PG) and the squared poverty gap index (SPG). The SPG is a distributionally sensitive measure that puts more weight on the people furthest below the poverty line, while HH and PG are not distributionally sensitive. The other two measures are the MPI, which is based on Alkire and Foster (2011) and Alkire et al. (2015), and the multidimensional distribution-sensitive poverty index (MDPI) developed by Datt (2019). As the name implies, the MDPI is distributionally sensitive while the MPI is not. The detailed formulae for these five indices are provided in Appendix A, with full details on the survey data used to construct them in Najam (2020). For money-metric poverty measures, this involves Elbers et al. (2003) approach to project consumption data from the Household Income and Expenditure Survey (HIES) onto the sample of the Pakistan Social and Living Standard Measurement Surveys (PSLM) that lacks consumption data, using sets of predictor variables from the two surveys that overlap. PLSM surveys are representative at district level, and are used to directly calculate the multidimensional poverty measures. This survey-to-survey imputation approach provides district-level money-metric poverty estimates. Full details are available in Najam (2020). For our purposes here, it is sufficient to note that we have estimates at district level for every second year, from 2004 to 2014.

According to Figure 1, the headcount poverty rate was around 40% in 2004 and 2006 but rose to almost 50% in 2008 (Figure 1). This sharp increase in poverty is due to the world food price surge in 2008, in which Pakistan's annual inflation increased from 7.7% in 2007 to 21% in 2008. These increases were followed by an even sharper fall, to about 25% in 2010, with a slight decline in 2012 and then a further sharp decline to below 15% by 2014. The movements of the poverty gap index were even more pronounced, rising faster from 2006 to 2008 and then declining even faster than what the movements in headcount poverty index show. The patterns for SPG are similar but with less sharp movements, so the overall patterns revealed by the money-metric measures is that poverty rates in 2014 were substantially lower than in 2004, albeit with an initial period of rising poverty, especially in 2008.

Figure 1: Average Poverty Estimates at the District Level and Number of BISP Beneficiaries for Six Alternative Years, 2004 - 2014



Source: Najam (2020)

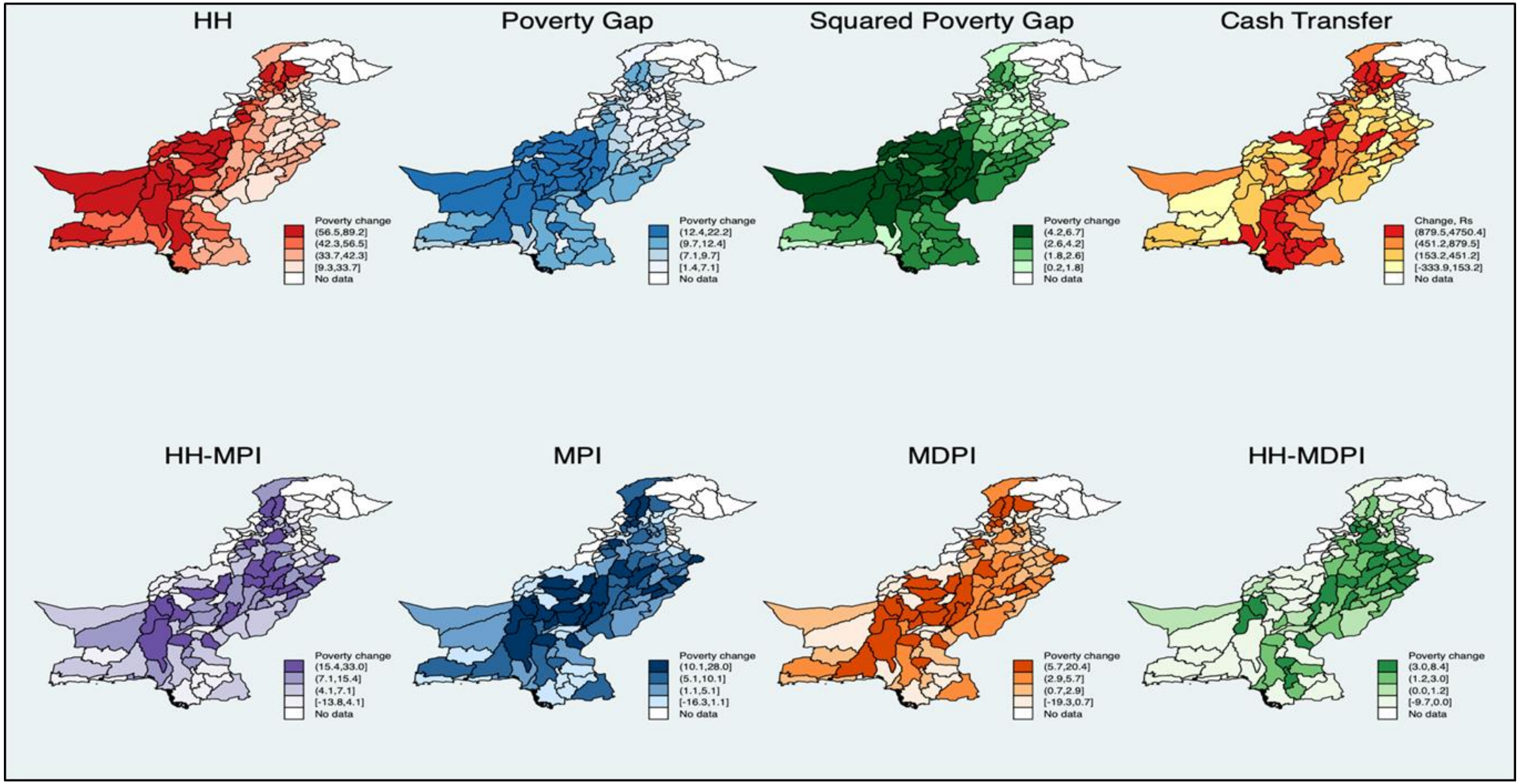
The multidimensional poverty measures present quite a different picture. There was a slow decline in the MPI, with an average index value of about 30% in 2004 declining to be just above 20% by 2014. The average level of the MDPI starts lower but does not decline quite as fast and neither measure shows any jump in 2008, unlike the fluctuations seen with the money-metric measures. The trends shown in Figure 1 relate to averages over all 100 districts (and years) but a disaggregated analysis by Najam (2020) also shows that the time trends in poverty in Pakistan depend on what sort of measures are used; over two-thirds of the districts show opposite trends in poverty rates, if using multidimensional measures rather than money-metric ones, for at least two of the five spells between the six survey waves. Figure 1 also shows that number of the BISP has increased substantially from 1.76 million in 2008 to 5.1 million beneficiaries in 2014.

To capture spatial heterogeneity within the country, in Figure 2 we present district-level maps of the change in the poverty rates over the 2008 to 2014 period for the five poverty measures and coverage of the BISP cash transfer. The darker colours on the map denote districts that had the fastest rates of poverty reduction. There are also some districts with no data, mainly in the Federally Administered Tribal Areas (FATA), where the PSLM surveys were not fielded due to the security situation. A group of neighbouring districts in *Balochistan* province (in the southwest) are among those with the least reduction in money-metric poverty measures over 2008-2014 after having the highest poverty rates in 2008. The larger physical size of some of these districts draws attention to them but it is also the case that the majority of districts with the least poverty reduction are in *Balochistan* because these were the districts that had highest rates of poverty in 2008.

In contrast to the maps for money-metric poverty measures, where the slowest rates of poverty reduction are mostly in *Punjab*, *Sindh* and a few scattered parts of *Khyber Pakhtunkhwa*, the multidimensional poverty measures show patterns that are more spatially random. The slowest rates of reduction in multidimensional poverty includes parts of *Sindh* and *Balochistan* provinces, plus some districts from *Khyber Pakhtunkhwa*.

In terms of the changes in coverage for the cash transfer, the map shows that majority of districts in *Sindh* province (in the southeast) and few districts in the *Khyber Pakhtunkhwa* province are among those with the highest increase in terms of per capita cash transfer between 2008-2014, while there seems to be a reduction in terms of coverage of the BISP in several districts within the *Punjab* province.

Figure 2: Change in Poverty Estimates and Cash Transfer Coverage for the Districts between 2008 – 2014



Notes: HH, Headcount Index; HH-MPI, Alkire & Foster (2011) Multidimensional Headcount Index; HH-MDPI, Multidimensional Distribution-sensitive Headcount Index; Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index; Cash Transfer (per capita) (BISP). Poverty changes are pre-BISP minus post-BISP

4. Empirical Methodology

The focus of this study is to investigate the impact of BISP in eradicating money-metric and multidimensional poverty at the district level of Pakistan based on the assumptions of counterfactual reasoning as we are evaluating the impact of social programme which has been implemented. The analysis is done in two stages. In the first stage, we employ the counterfactual decomposition technique introduced by Blinder and Oaxaca to examine: (i) if the same trends in poverty are apparent if one uses either the conventional or the multidimensional measures before and after the implementation of the BISP and (ii) whether the reduction in poverty is due to result of improvement in factors such as infrastructure or due to BISP. In the second stage, the impact of cash transfers in reducing poverty using conventional and non-conventional poverty measures is estimated along with investigating which targeting regimes (CBT vs PMT) worked better.

4.1 Blinder- Oaxaca Decomposition

The Blinder- Oaxaca Decomposition has been most frequently applied in labour economics to explain wage differentials between groups, such as males and females, immigrants and natives and black and white workers. It decomposes the average difference between two groups into three components. The first component explains the difference between two groups due to differences in their endowments (the covariates in the wage equation). The second component refers to the difference due to different returns to these characteristics (that is, differences in the coefficients of the wage equations). It is this second component that can indicate the presence of gender or racial biases, whereby people with the same characteristics receive different payoffs. The third component is the combination of endowments and coefficients, and is known as the interaction component.

In this paper, we use the Blinder-Oaxaca decomposition method to investigate if there is any significant difference in the average poverty estimates before and after the implementation of the BISP. The decomposition technique allows the identification of how much of mean differences on outcomes across two time periods can be explained by the differences in observed characteristics. The rest of differences that cannot be explained by observed characteristics can be defined as exogenous effects. In this light, the Blinder–Oaxaca decomposition can be applied in policy evaluation to estimate the net policy impact (Hwang and Lee, 2015)

To identify the policy impact of BISP on poverty using the Blinder-Oaxaca decomposition, linear regression defined by equation (1) is divided into two groups: ‘pre’ BISP and ‘post’ BSP. In the first equation, the poverty estimates from the first group ‘pre’, before 2008, are regressed on a set of covariates. In the second equation, the poverty estimates from the second group, ‘post’, calculated using conventional and non-conventional poverty estimates are regressed on covariates post 2008. The covariates used in both these regressions include household characteristics, access to services and facilities that define the living standard of a household such as electricity, gas, access to water, access to hospitals, schools, number of rooms, brick wall, number of rooms.

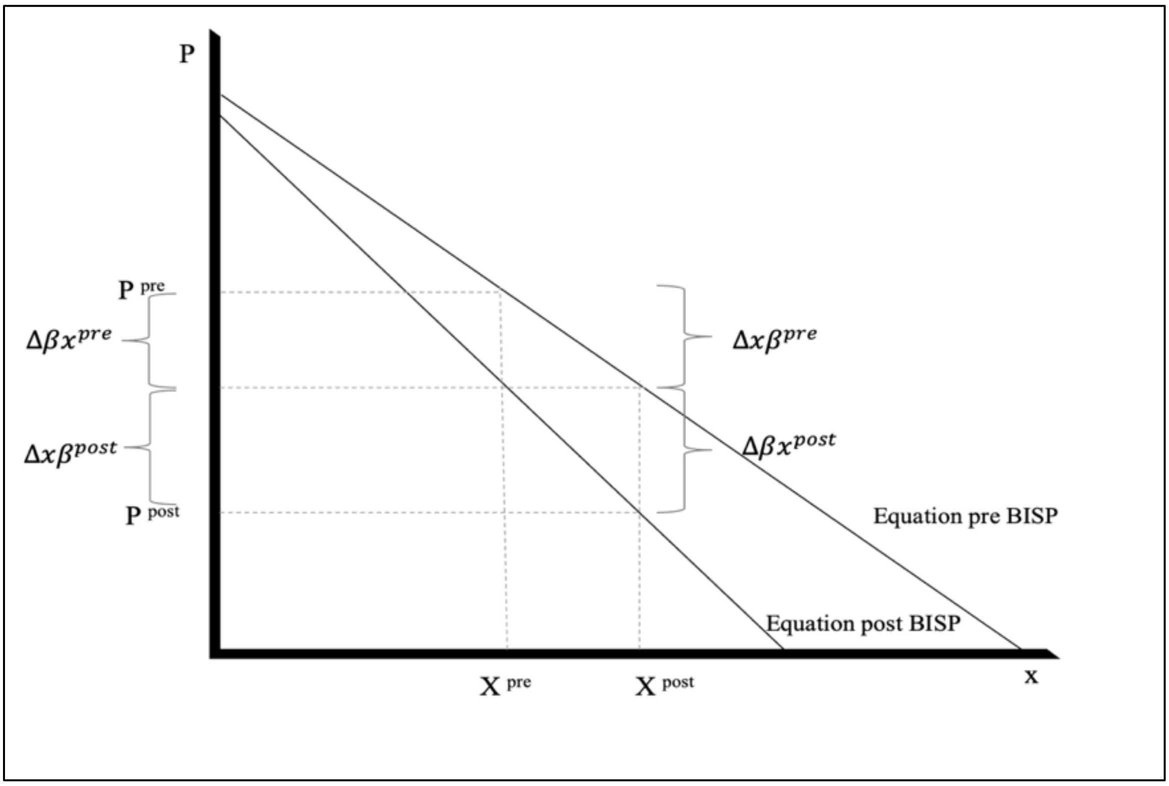
$$P_i = \begin{cases} \beta^{pre} x_i + \varepsilon_i^{pre} & Pre\ BISP \\ \beta^{post} x_i + \varepsilon_i^{post} & Post\ BISP \end{cases} \tag{1}$$

where x_i is the set of covariates, P_i is the money metric and multidimensional poverty estimates. The difference in the average poverty estimates for two groups, pre- and post- BISP can be expressed as:

$$p^{pre} - p^{post} = \beta^{pre} x^{pre} - \beta^{post} x^{post} \tag{2}$$

A simple graphical representation is presented in Figure 3, with poverty as the outcome variable and for simplicity we assume a single covariate, *x*, such as number of rooms, which is negatively associated with poverty; and the mean level of *x* in post-BISP is higher than that of in the pre-BISP because of the improvements in social indicators over time (World Bank, 2016).

Figure 3: Graphical representation of Blinder-Oaxaca decomposition



We assume that the difference in average poverty estimates between two groups is not merely because of the difference in the value of covariates, $\Delta x\beta^{pre}$, but is also due to the difference in effects of those covariates, the slope of the model, $\Delta\beta x^{post}$. The above figure implies the following:

$$p^{pre} - p^{post} = \Delta\beta x^{post} + \Delta x\beta^{pre} \quad (3)$$

where,

$$\Delta x = x^{\text{pre}} - x^{\text{post}}$$
$$\Delta\beta = \beta^{\text{pre}} - \beta^{\text{post}}$$

Expanding equation (3) leads to the following equation. The derivation is given in Annex B.

$$p^{pre} - p^{post} = (x^{\text{pre}} - x^{\text{post}})\, \beta^{\text{post}} + (\beta^{\text{pre}} - \beta^{\text{post}})\, x^{\text{post}} + (x^{\text{pre}} - x^{\text{post}})\, (\beta^{\text{pre}} - \beta^{\text{post}}) \quad (4)$$

Equation (4) shows the threefold decomposition of the average difference in poverty estimates for two groups. The difference $p^{pre} - p^{post}$ is decomposed into three parts: (i) endowments $(x^{\text{pre}} - x^{\text{post}})\, \beta^{\text{post}}$, (ii) coefficients $(\beta^{\text{pre}} - \beta^{\text{post}})\, x^{\text{post}}$ and (iii) interaction $(x^{\text{pre}} - x^{\text{post}})\, (\beta^{\text{pre}} - \beta^{\text{post}})$. Endowments constitute the differences caused due to the change in covariates (x) post- and pre- BISP. Coefficients constitute the difference caused due to factors other than changes in endowment and/or covariates. In our study, because the demarcation between two groups is because of the initiation of a social safety net program, BISP, any difference caused by the coefficient component indicates towards BISP. The third component, interaction, refers to the difference caused because of the coexistence of endowments and coefficients.

Given the declining trend of poverty estimates for conventional and non-conventional poverty measures (Najam, 2020), we can observe if the reduction in poverty using both conventional and non-conventional poverty measures between 2004-2006 and 2008-2014 is a result of economic development in terms of increased access to services and facilities (i.e. endowments component) or there is an unexplained component to it as well (i.e. coefficients component).

4.2 Panel Regressions

Once we have a significant coefficient component from the Blinder-Oaxaca decomposition, we run a panel regression on the period post inception of the BISP in 2008. In the presence of control variables, the panel regression shows how influential the cash transfers are in reducing the poverty estimates generated through money-metric and multidimensional approaches, in which some of them comply to the axiom of distribution sensitivity. As explained earlier, BISP had two targeting phases, from 2008-2010 it relied on CBT and post 2010 it relies on PMT. In our analysis, it is important to observe whether changing the targeting approach has any significant impact in reducing poverty at the district level. We want to observe whether the effect of Cash Transfer (CT) on poverty estimates changes (+/-) when there is a change in the targeting approach. To factor this in, we also included an intercept dummy $(Phase)$ and interactive dummy $(CT_{it}) * (Phase)$. Hausman test is applied to select the appropriate structure of panel model for each poverty measure. Equations 5.1 and 5.2 represent the structural form of fixed effect panel while those for the random effect are shown in equation 5.3 and 5.4.

$$P_{it} = \alpha + \beta(CT_{it}) + \gamma(x_{it}) + \delta(D_i) + \varepsilon_{it} \tag{5.1}$$
$$P_{it} = \alpha + \beta(CT_{it}) + \gamma(x_{it}) + \eta(Phase) + \delta(D_i) + \theta(CT_{it})(Phase) + \varepsilon_{it} \tag{5.2}$$
$$P_{it} = \alpha + \beta(CT_{it}) + \gamma(x_{it}) + \delta(D_i) + U_{it} + \varepsilon_{it} \tag{5.3}$$
$$P_{it} = \alpha + \beta(CT_{it}) + \gamma(x_{it}) + \delta(D_i) + \eta(Phase) + \theta(CT_{it})(Phase) + u_{it} + \varepsilon_{it} \tag{5.4}$$

where

P_{it} = Poverty estimates for district *i* in time *t*
CT_{it} = Cash transfers for district *i* in time *t*
x_{it} = Set of control variables that falls into the broader categories of household demographics, education, health, living standards and access to facilities
D_i = District dummy in fixed effect model
$Phase$ = Dummy for the change in targeting phase which takes value of 1 if CBT and 0 if PMT
ε_{it} = Error term
u_{it} = Between districts error term in random effect model

5. Results

Prior to analysing the effect of BISP cash transfer on poverty and whether choice of poverty measure matter, we compared the coverage of the cash transfer at the district level across four alternate years. Appendix C provides spatial profile of both money metric and multidimensional poverty estimates along with the amount of cash transfers at the district level for four alternate survey years of 2008, 2010, 2012 and 2014.

The districts which have the highest poverty estimates whether using conventional or non-conventional poverty measures do not completely fall into the list of districts which received highest per capita cash transfers. Even after 2010 when the targeting approach was changed to PMT, the districts which have the highest incidence of poverty based on money-metric poverty measures (headcount) are not falling into the highest cash receiving tier. If we consider the headcount of the multidimensional poverty estimates, the districts with highest incidence of poverty which are concentrated in the south-west of Pakistan (*Balochishtan* province) are not receiving the highest amount of cash transfers. BISP does not seem to be targeting districts with highest incidence of poverty even if we just consider the spatial profile using headcount indices. If we consider complex poverty measures which are sensitive to the depth and distribution of the poverty, the coverage of BISP seems even less well targeted.

Although there is poor overlap between the coverage of BISP and the poverty measures, it is important to observe if there is any significant difference in average poverty estimates before and after the start of the largest social safety net program in Pakistan. In particular we want to examine the effects of factors other than changes in household endowments. To examine the drivers of poverty reduction, Table 4 reported Blinder-Oaxaca decomposition for not only money-metric but also multidimensional poverty measures.

For money-metric poverty measures, it showed that there was a relatively large decline in poverty of about 12.33 percentage points for monetary HH poverty measure. Similar magnitude of poverty reduction was observed if using the distributional insensitive multidimensional poverty index MPI (a reduction of 10.21 percentage points). Appendix D provides the Blinder-Oaxaca decomposition results in details.

Table 4: Drivers of poverty reduction: Decomposing changes in poverty

Poverty Measures		Difference	Endowment	Coefficient	Interaction
Money Metric	Distribution Insensitive				
	Headcount Index (HH)	12.33*** (1.82)	5.94 ** (3.02)	5.64 *** (2.08)	0.74 (3.19)
	Poverty Gap Index (PG)	2.85 *** (0.44)	1.0 *** (0.37)	1.72 *** (0.45)	0.13 (0.39)
	Distribution Sensitive				
	Squared Poverty Gap Index (SPG)	0.80 *** (0.13)	0.28 *** (0.10)	0.51 *** (0.14)	0.02 (0.12)
Multidimensional	Distribution Insensitive				
	Multidimensional Poverty Index (MPI)	7.02 *** (1.31)	5.52 *** (1.3)	0.81 (0.63)	0.69 (0.57)
	Headcount MPI	10.21 *** (1.88)	8.04 *** (1.89)	1.06 (0.77)	1.10 (0.69)
	Distribution Sensitive				
	Multidimensional Distribution-sensitive Poverty Index (MDPI)	4.72*** (0.90)	2.58 *** (0.82)	1.13 (0.86)	1.00 (0.81)
	Headcount MDPI	2.03 *** (0.60)	1.55 * (0.43)	0.42 (0.56)	0.05 (0.36)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level. The differences in poverty estimates are pre-BISP minus post-BISP (hence the positive sign of poverty reduction)

For all of our poverty measures irrespective of whether they are money metric or multidimensional or distribution sensitive, they have shown decrease in poverty estimates after the cash transfers. The reduction in poverty is the greatest for the HH (a 12.33 percentage reduction). The statistically significant effect of endowment component indicates the difference in poverty estimates between two periods is because of the difference in endowments that households possess. The development projects and/or initiatives have increased in numbers and in value over time, which is helpful in uplifting the living standards of Pakistani people and ultimately decreasing the level of poverty, represented through endowment component. Various development projects were put in place during these periods, which include construction of degree colleges for girls in different villages and towns, construction of centres in hospital for transplantation and blood transfusions, construction of training and welfare institutes, building of new roads under China-Pakistan Economic Corridor.[3] The development expenditure as percentage of GDP was 3.9 in 2004 which increased to 4.9% by 2014 (Ministry of Finance, 2018). The significant endowment component refers to this development as a source for poverty reduction. However, the significant coefficient component refers to the other unexplained factors beyond endowments. In our case the only factor that is creating two distinct groups is the presence of cash transfers. The significant coefficient component refers to the part of difference caused because of the cash transfers.

In the case of money metric poverty measures, the reduction in poverty estimates between two time periods is majorly due to the (coefficient) return on endowments which refers to the cash transfers in our case. Also, the money metric poverty measure, which account for the depth in poverty and distribution sensitivity axiom, is predominately reduced due to the return on endowments (cash transfers). The reduction in money-metric poverty measures over two periods is induced due to both the increase in endowments/ services/facilities available to the households and also due to the cash transfers made to the households. Hence, not only the development in the economy is helping households in increasing their consumption but also the cash transferred to the households is providing the support.

In the case of multidimensional poverty measures, the reduction in poverty estimates is caused due to the improvement/increase in endowments. The return on endowment (coefficient) though is positive but is insignificant. The factors other than increased access to services and facilities are not significant in reducing the multidimensional poverty estimates. The results showed that after 2008 when BISP was implemented, the reduction in multidimensional poverty estimates is due to increased / improved access to services and facilities. As the multidimensional poverty measures are based on the access to the services and facilities hence any improvement in those statistics must come from increase in assets, facilities and services available to the individuals. However, an explicit regression modelling has revealed the impact of cash transfers made to the households in uplifting the living standard and human capital of households (World Bank, 2016).

[3] The details on development projects in Pakistan can be found at https://www.pc.gov.pk/

The panel regression run on poverty measures at the district level post 2008 is shown in Table 5 below. Districts in Pakistan belong to different geographical and economic characteristics. For instance, some districts rely on agricultural, while other rely either on tourism as their revenue generating process. To take into account the heterogeneity across districts in Pakistan, we included district fixed effects in the model. The amount paid to the poor households has been revised over years which takes into account the changing economic conditions of the economy. The other covariates that we used control for the development initiatives that affects the access to services and facilities.

The coefficient of log cash transfer from the first model and the coefficients of dummy variables that accounts for different targeting process from the second model (Eq 5.2 and 5.4) for respective poverty measures are presented in Table 5 below. Detailed regression results are given in Appendix E

Table 5: Panel Regression Cash Transfer Coefficients for Poverty Measures' Models

		Model 1	Model 2		
	Poverty Measures	Log Cash Transfer	Log Cash Transfer	Log Cash Transfer × Phase I	Phase
Money Metric	Distribution Insensitive				
	Headcount Index - HH	-10.8*** (1.38)	-11.25*** (1.59)	-2.16* (1.28)	40.82* (24.43)
	Poverty Gap Index - PG	-1.93 *** (0.34)	-1.79*** (0.39)	-0.98*** (0.32)	18.70*** (6.15)
	Distribution Sensitive				
	Squared Poverty Gap Index - SPG	-0.49 *** (0.10)	-0.44*** (0.12)	-0.30*** (0.09)	5.69*** (0.12)
Multidimensional	Distribution Insensitive				
	Multidimensional Poverty Index - MPI	-0.98 ** (0.01)	-1.58*** (0.42)	1.34*** (0.34)	-24.62*** (6.57)
	Headcount MPI	-0.96 * (0.55)	-1.81** (0.55)	1.79*** (0.45)	-31.47*** (8.52)
	Distribution Sensitive				
	Multidimensional Distribution-sensitive Poverty Index - MDPI	-0.82 *** (0.26)	-1.21*** (0.27)	0.35*** (0.32)	-7.95 (6.10)
	Headcount MDPI	-0.28 * (0.16)	-0.19 (0.19)	0.26 (0.18)	-4.59 (3.44)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

All the poverty measures except MDPI have taken the form of fixed effect panel regression (based on Hausman test results). MDPI which is distribution sensitive has taken the form of random effect panel model. The random effect is plausible when there is influence of entities (districts) on the dependent variable. In our case there is a plausible influence of districts on the distribution sensitive MDPI as Khan and Sasaki (2003) identified the polarisation of development priorities in Pakistan. The development projects are concentrated on certain regions and constituencies, therefore, multidimensional poverty estimates which are distribution sensitive are affected by development status of the districts (Najam, 2020).

Two models are estimated. The second model considers different targeting regimes, which changed from the CBT to PMT after 2010. For both models, cash transfers for money-metric as well as multidimensional poverty measures are shown to have poverty reducing impact. The impact is stronger for conventional poverty measures. In the second model, the dummy variable is included to factor in the switch from the CBT to PMT. The results show that CBT process was stronger in reducing poverty when the poverty is estimated using conventional poverty measures. But if the researchers relied on non-conventional poverty measures they are going to infer that the PMT targeting process was more effective in reducing poverty than the CBT. The reason for the stronger effect of BISP in reducing multidimensional poverty in the second targeting phase is because the Poverty Score Card used for screening and identifying poor households asked questions which are related to assets/ services/ facilities available to the individuals. Those are the variables used in constructing multidimensional poverty measures. That means if the screening and identification have questions related to consumption or income, it will closely target poor households which would also be identified using money-metric poverty measures.

However, if we just consider the impact of cash transfers in reducing poverty, the impact is significant for money-metric and multidimensional poverty measures except for the Multidimension Distribution-sensitive Poverty Headcount. One thing to note here is that the unconditional cash transfers is not just reducing the poverty through increasing consumption but also through uplifting living standards. Dietrich et al. (2020) in their study on Uganda showed that there is positive impact of cash transfers on human capital. In our case, the plausible explanation is that the improved financial conditions help the households to invest in not just human capital but also in other facilities which help in reducing multidimensional poverty estimates. There has been a criticism on the unconditional cash transfer programmes in that they fail to provide sustained means of livelihood to the beneficiaries (Molyneux et al., 2016). Multidimensional poverty measures which are calculated using indicators/variables which are responsible to provide sustainable means of likelihood to the individuals have shown improvement after the unconditional cash transfers were made. This analysis helped in putting aside the concern of researchers that unconditional cash transfers does not help in promoting sustainable consumption/investment decisions.

It follows that anti-poverty programmes which involve unconditional financial support to poor families also have an influence on enhancing capabilities of individuals. Multidimensional poverty measures which are developed on capability approach have shown reduction due to increase in cash transfers. There is one more point that needs attention. In this analysis, the distribution sensitive multidimensional poverty measure has taken the random effect form which means that district characteristics could have influence on MDPI.

The polarisation of infrastructure development in certain districts have deteriorated the capabilities set of individuals in deprived districts. Hence, the concentration of high MDPI estimates in less developed districts is observed. Therefore, the depolarisation of development priorities in districts is crucial for increasing the access to services and facilities and for the effects of cash transfers to spread across.

6. Conclusions

To ensure that social safety net programs reach the poorest segment of the society, analysis is required to observe how effective those programs are in alleviating poverty over time. Given that there is evidence of poverty trends across time being sensitive to the choice of poverty measure, it is thus necessary to check for the sensitivity of the effect of cash transfer in alleviating poverty.

In this paper, we use five poverty measures, calculated biennially from 2008 to 2014 for 100 districts in Pakistan to assess the effectiveness of the BISP in alleviating poverty. We also examine whether the impact of the cash transfer programs on poverty is sensitive to the choice of poverty measure. Our results show that poverty reducing effects of BISP is not just money metric but also multidimensional poverty measures. However, the effect of BISP is stronger in reducing conventional poverty estimates as compared to the non-conventional poverty estimates. One important thing to conclude from the results is that if we consider the concept of depth, intensity and distribution sensitivity in quantifying poverty, more support in terms of cash transfers is required to eradicate poverty. Our findings also support that households are using the cash received not for consumption only, but also use the cash in improving their living standards.

Under the current BISP system, a set amount of cash is paid to the eligible households irrespective of how many people are living in the household or how deprived the household is. In order to reach out to the poorest households with the sufficient support, the distribution sensitive poverty measures should be considered in identifying and targeting the households. Increasing the amount of cash transfers on the basis of the depth/intensity of deprivation should be considered by policy makers.

In terms of comparison between the two targeting approaches used, the results showed that CBT was more effective in reducing money-metric poverty estimates whereas PMT was better in reducing multidimensional poverty estimates. It is recommended here that the poverty score card which is used to identify the poor households should at least include some information on consumption/income component in the survey. It is important to add these aspects into the identification survey because from the study by Saleem (2020) on a district in the *Khyber Pakhtunkwa* Province, there were a few households which were struggling financially and yet did not meet the PMT criterion. Consequently, if a household has basic assets and facilities listed under Poverty Score Card but is struggling to meet its ends, it will not make the eligibility criterion. The point is that the households which are financially constrained may not be eligible for the benefit because they are evaluated on a totally different criterion which only consider assets, access to services and facilities but not consumption. In Pakistan, it is difficult to sell the assets to meet the consumption needs hence in the Poverty Score Card surveys we can observe the presence of few assets but not necessarily have the means to meet the consumption.

References

Acosta, P. A., & Velarde, R. B. (2015). *An update of the Philippine conditional cash transfer's implementation performance* (Social Protection Policy note No. 8). Washington, D.C.: World Bank Group.

Afzal, A., Nawazish, M., & Arshad, F. (2019). Conditional vs unconditional cash transfers: a study of poverty demographics in Pakistan. *Economic research - Ekonomska istraživanja, 32* (1), 3360-3377.

Akresh, R., De Walque, D., & Kazianga, H. (2013). *Cash Transfers and Child Schooling : Evidence from a Randomized Evaluation of the Role of Conditionality* (Policy Research Working Paper No. 6340). Washington, D.C.: World Bank.

Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics*, 95(7), 476-487.

Alkire, S., & Jahan, S. (2018). *The new global MPI 2018: Aligning with the Sustainable Development Goals* (OPHI Working Paper No. 121). University of Oxford.

Alkire, S., Roche, J. M., Ballon, P., Foster, J., Santos, M. E., & Seth, S. (2015). *Multidimensional Poverty Measurement and Analysis.* Oxford University Press, USA.

Amrin, S., & Ashfaq, M. (2020). The impact of Benazir Income Support Program BISP on household food expenditures in Faislabad. *Pakistan Journal of Agricultural Sciences, 57*(1), 275-279.

Attanasio, O. P., Meghir, C. & Santiago, A. (2011). Education choices in Mexico: Using a structural model and a randomized experiment to evaluate Progresa. *The Review of Economic Studies, 79*(1), 37-66.

Azeem, M. M., Mugera, A. W., & Schilizzi, S. (2019). Do Social Protection Transfers Reduce Poverty and Vulnerability to Poverty in Pakistan? Household Level Evidence from Punjab. *The Journal of Development Studies, 55*(8), 1757-1783.

Benazir Income Support Programme (n.d.). *Unconditional Cash Transfer (UCT) Programme*. Accessed from, https://www.bisp.gov.pk/Detail/ZTljNWY2NWUtODYwNC00MjVjLWFiODUtMDRhOGI0OTI5NzUw

BISP (Benazir Income Support Programme). (2016). Benazir Income Support Programme website. Accessible at: http://www.bisp.gov.pk/

Cheema, I., Farhat, M., Hunt, S., Javeed, S., Keck, K., & O'Leary, S. (2015). *Benazir income support programme: Second impact evaluation report*. Oxford, UK: Oxford Policy Management.

Datt, G. (2019). Distribution-sensitive multidimensional poverty measures. *The World Bank Economic Review, 33*(3), 551-572. https://doi.org/10.1093/wber/lhx017

De Brauw, A., & Hoddinott, J. (2011). Must Conditional Cash Transfer Programs be Conditionedto be Effective? The Impact of Conditioning Transfers on School Enrolment in Mexico. *Journal of Development Economics, 96*(2), 359-370.

Devereux, S. (2002). Can Social Safety Nets Reduce Chronic Poverty?. *Development Policy Review, 20*(5), 657-675. doi:https://doi.org/10.1111/1467-7679.00194

Dietrich, S., Malerba, D., Barrientos, A., Gassmann, F., Mohnen, P., & Tirivayi, N. (2020). Human capital returns to cash transfers in Uganda: does it matter in the long run?. *Journal of Development Effectiveness, 12*(1), 54-73.

Elbers, C., Lanjouw, J. O., & Lanjouw, P. (2003). Micro-Level Estimation of Poverty and Inequality. *Econometrica, 71*(1), 355-364. Retrieved from www.jstor.org/stable/3082050

Fiszbein, A., Schady, N. , Ferreira, F. H. G., Grosh, M., Keleher, N., Olinto, P., & Skoufias, E. (2009). *Conditional Cash Transfers: Reducing Present and Future Poverty*. Washington, DC: World Bank.

Fosu, A. (2011). Growth, inequality, and poverty reduction in developing countries: Recent global evidence. *SSRN Electronic Journal, 43*(1), 44–59.

Gazdar, H., & Zuberi, S. (2014). Final Report of the Beneficiary Feedback Survey, National Cash Transfer Programme–Pakistan. Karachi: Collective for Social Science Research. Available at: http://www.researchcollective.org/Documents/Updated_Anonymised_BFS_Final_Report_03022014.pdf

Gertler, P., & Boyce, S. (2003). An Experiment in Incentive-Based Welfare: The Impact of PROGRESA on Health in Mexico, Working Paper. University of California Berkeley, CA.

Grosh, M., Del Ninno, C., Tesliuc, E., & Ouerghi, A. (2008). *For Protection and Promotion : The Design and Implementation of Effective Safety Nets.* Washington, DC : World Bank.

Harrison, C. (2019). *Do Cash Transfers Increase Savings by the Poor? Evidence from Mexico's Progresa/Oportunidades Program.* Georgetown University.

Haushofer, J., & Shapiro, J. (2016). The Short-term Impact of Unconditional Cash Transfers to the Poor: Experimental Evidence from Kenya. *The Quarterly Journal of Economics, 131*(4), 1973–2042.

Hwang, J. & Lee, S. (2015). The Effect of the Rural Tourism Policy on Non-farm Income in South Korea. *Tourism Management*, 46, 501–513

Junaid Z., & Mohsin K., (2017). *How Government Funds Help To Reduce Poverty?: A Case Study of CIF & BISP in Sindh (Working Papers No. 161).* SDPI.

Khan, M. T. Y., & Sasaki, K. (2003). Regional Disparity in Pakistan’s Economy: Regional Econometric Analysis of Causes and Remedies. *Interdisciplinary Information Sciences, 9*(2), 293-308.

Kidd, S., & Wylde, E. (2011). *Targeting the Poorest: An Assessment of the Proxy Means Test Methodology* (AusAID Research Paper). Canberra, Australia: Australian Agency for International Development .

Kremer, M., Brannen, C., & Glennerster, R. (2013). The Challenge of Education and Learning in the Developing World. *Science,* 340 (6130), 297–300.

Lee, K. W., & Park, C. (2002). Globalization, growth, inequality, and social safety nets in APEC Economics. *Asian Development Review*, *19*(2), 47-66.

Merttens, F., Sindou, E., Lipcan, A., Pellerano, L., Binci, M., Ssewanyana, S., & Neema, S. (2016). Uganda - Social Assistance Grants for Empowerment Programme 2014, Endline: Impact After Two Years of Programme Operations. London: Oxford Policy management.

Ministry of Finance (MoF). (2018). *The Economic Survey of Pakistan 2018*. Government of Pakistan.

Molyneux, M., Jones, W., & Samuels, F. (2016). Can cash transfer programmes have 'transformative' effects?. *The Journal of Development Studies*, *52*(8), 1087–1098.

Najam, Z. (2020). *The Sensitivity of Poverty Trends to Dimensionality and Distribution Sensitivity in Poverty Measures – District level Analysis for Pakistan*. Retrieved from https://EconPapers.repec.org/RePEc:pra:mprapa:102383

Nayab, D., & Farooq, S. (2014). Effectiveness of cash transfer programmes for household welfare in Pakistan: The case of the Benazir Income Support Programme. *Pakistan Development Review*, 53(2), 145.

Pasha, M. A., Shah, P., & Rahpoto, M. S. (2018). Effectiveness of Benazir Income Support Program for Poverty Reduction. *Global Management Journal for Academic & Corporate Studies*, *8*(2), 144-149.

Pritchard, B., Rammohan, A., Sekher, M., Parasuraman, S., & Choithani, C. (2013). *Feeding India: Livelihoods, entitlements and capabilities*. Routledge.

Ravallion, M. (2001). Growth, inequality and poverty: Looking beyond averages. *World Development*, *29*(11), 1803–1815.

Ravallion, M. (2004). *Pro-Poor Growth: A Primer* (Working Paper No. 3242). World Bank, Washington, D.C. © World Bank. https://openknowledge.worldbank.org/handle/10986/14116 License: CC BY 3.0 IGO.

Saleem, M. (2019). Evaluating political capture and targeting performance of the Benazir Income Support Program in Pakistan (Doctoral Dissertation, Erasmus University Rotterdam).

Schultz, T. P. (2004). School Subsidies for the Poor: Evaluating the Mexican Progresa Poverty Program. *Journal of Development Economics, 74*(1), 199–250.

World Bank (2009). *Project Appraisal Document on a Proposed Credit to the Islamic Republic of Pakistan for a Social Safety Net* (Technical Assistance Project No. 47288-PK).

World Bank (2016). *Pakistan Development Update*. Washington, DC: World Bank.

World Bank (2018). *The State of Social Safety Nets 2018*. Washington, DC: World Bank.

Appendix A

Table A1: Description of the Five Poverty Measures Used in the Study

Poverty Measures	Description
Money-Metric	
Distribution Insensitive	
Headcount Index: $HH = (q/n) \times 100$	where q is the number of poor people living below the poverty line and n is the total number of people. HH is the proportion of people living below the poverty line.
Poverty Gap Index: $PG = \frac{\left(\sum_{i=1}^{n}\left(\frac{Z - Y_i}{Z}\right)\right)}{n} \times 100$	where Z is the poverty line and Y_i is individual i's consumption. PG measures the intensity of poverty in a given society.
Distribution Sensitive	
Squared Poverty Gap: $SPG = \frac{\left(\sum_{i=1}^{n}\left(\frac{Z - Y_i}{Z}\right)^2\right)}{n} \times 100$	where Z is the poverty line and Y_i is individual i's consumption. SPG averages the squares of poverty gaps relative to the poverty line and it gives heavier weight than the PG to the poverty of the very poor
Multidimensional	
Distribution Insensitive	
Multidimensional Poverty Index $MPI = \mathrm{M}(\alpha, \mathrm{k}; \mathrm{y}) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{d}\sum_{j=1}^{d} g_{ij}^{\alpha}\right) I_i^k \times 100$	For n individuals and d total dimensions, $g_{ij}^{\alpha} = (1 - y_{ij}/z_j)^{\alpha} I_{ij}$ for $\alpha \geq 0$ is the indicator for deprivation for an individual i in dimension j. z_j is the cut-off point for the dimension j. $I_i^k = I(C_i \geq k)$ is the poverty indicator in which k is the cut-off number of dimensions in which an individual has to be deprived to be poor and C_i is the total dimensions in which an individual i is deprived and denoted as $C_i = \sum_{j=1}^{d} I_{ij}$
Distribution Sensitive	
Multidimensional Distribution-Sensitive Poverty Index $\mathrm{MDPI} = \mathrm{M}(\alpha, \beta; \mathrm{y}) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{1}{d}\sum_{j=1}^{d} g_{ij}^{\alpha}\right)^{\beta} \times 100$ for $\alpha \geq 0$ and $\beta \geq 1$	For $\beta > 1$, the measure $\mathrm{M}(\alpha, \beta; \mathrm{y})$ satisfies the cross-dimensional convexity axiom, where: $g_{ij}^{\alpha} = (1 - y_{ij}/z_j)^{\alpha} I_{ij}$ for $\alpha \geq 0$ and y_{ij} is the individual i's score in dimension j and z_j is the cutoff point for deprivation j. $I_{ij} = I(y_{ij} < Z_j)$ 0 – 1 deprivation indicator function and I_{ij} takes value of zero when $y_{ij} > z_j$; and 1 when $y_{ij} \leq z_j$

Appendix B: Blinder-Oaxaca Decomposition Derivation

$p^{pre} - p^{post} = \beta^{pre}x^{pre} - \beta^{post}x^{post}$ ……………………………………………..……1

Add and subtract the following from the equation 1

$\beta^{post}x^{post}$
$\beta^{pre}x^{post}$
$\beta^{post}x^{pre}$

Resulting into equation 2

$p^{pre} - p^{post} = \beta^{pre}x^{pre} - \beta^{post}x^{post} + (\beta^{post}x^{post} - \beta^{post}x^{post}) + (\beta^{pre}x^{post} - \beta^{pre}x^{post}) + (\beta^{post}x^{pre} - \beta^{post}x^{pre})$ ……………………………………….…...…..2

Rearrange the equation 2

$p^{pre} - p^{post} = (x^{pre} - x^{post})\,\beta^{post} + (\beta^{pre} - \beta^{post})\,x^{post} + (x^{pre} - x^{post})\,(\beta^{pre} - \beta^{post})$……….3

The equation 3 can be written as follows
$p^{pre} - p^{post} = \Delta x\beta^{post} + \Delta\beta x^{post} + (x^{pre} - x^{post})\,(\beta^{pre} - \beta^{post})$ ……………..……………4

Whereas;

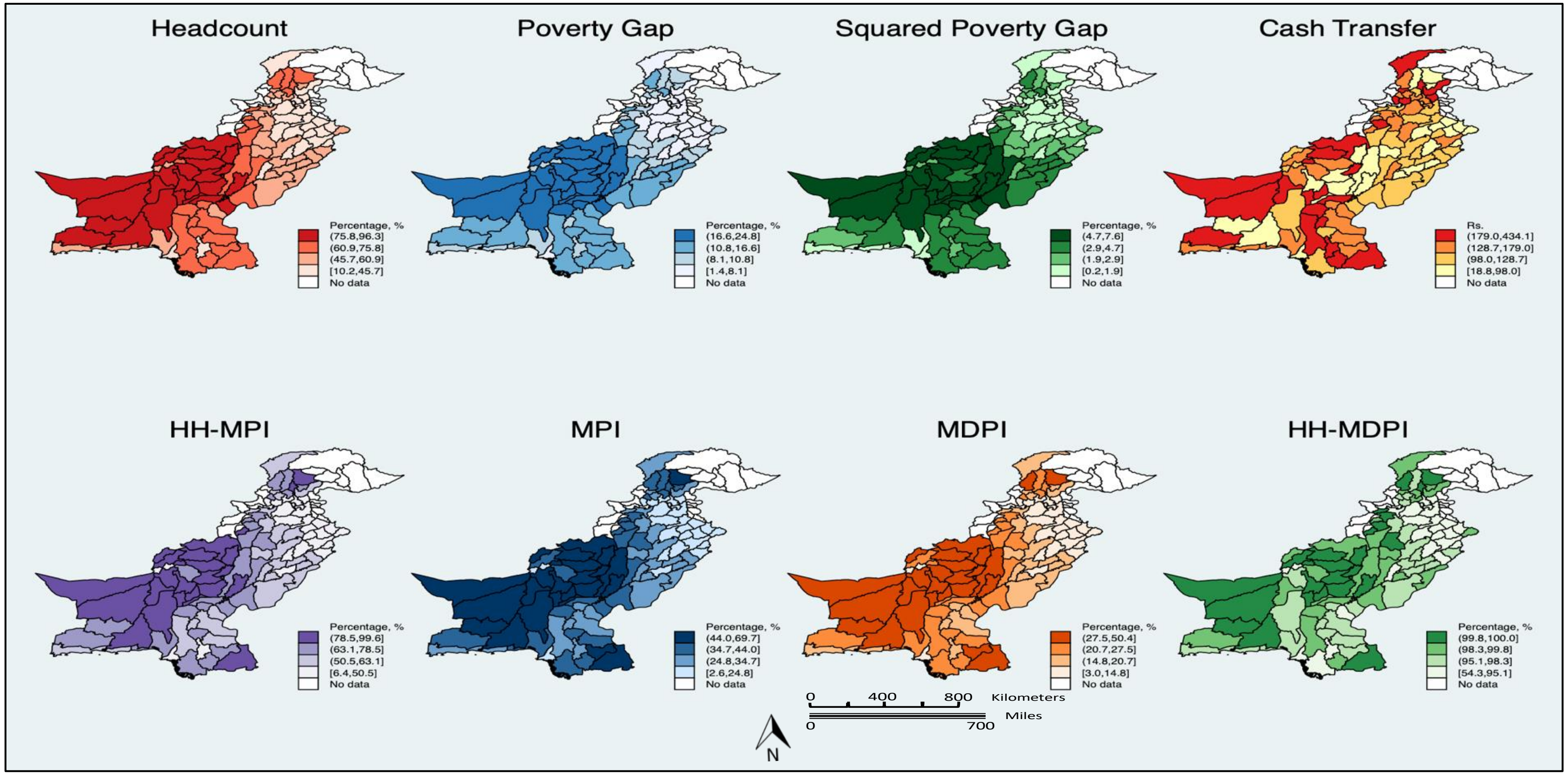
$\Delta x = x^{pre} - x^{post}$
$\Delta\beta = \beta^{pre} - \beta^{post}$

The following are the three decomposed components from Blinder-Oaxaca decomposition

1. $Endowment = \Delta x\beta^{post}$
2. $Coefficient = \Delta\beta x^{post}$
3. $Interaction = (x^{pre} - x^{post})\,(\beta^{pre} - \beta^{post})$

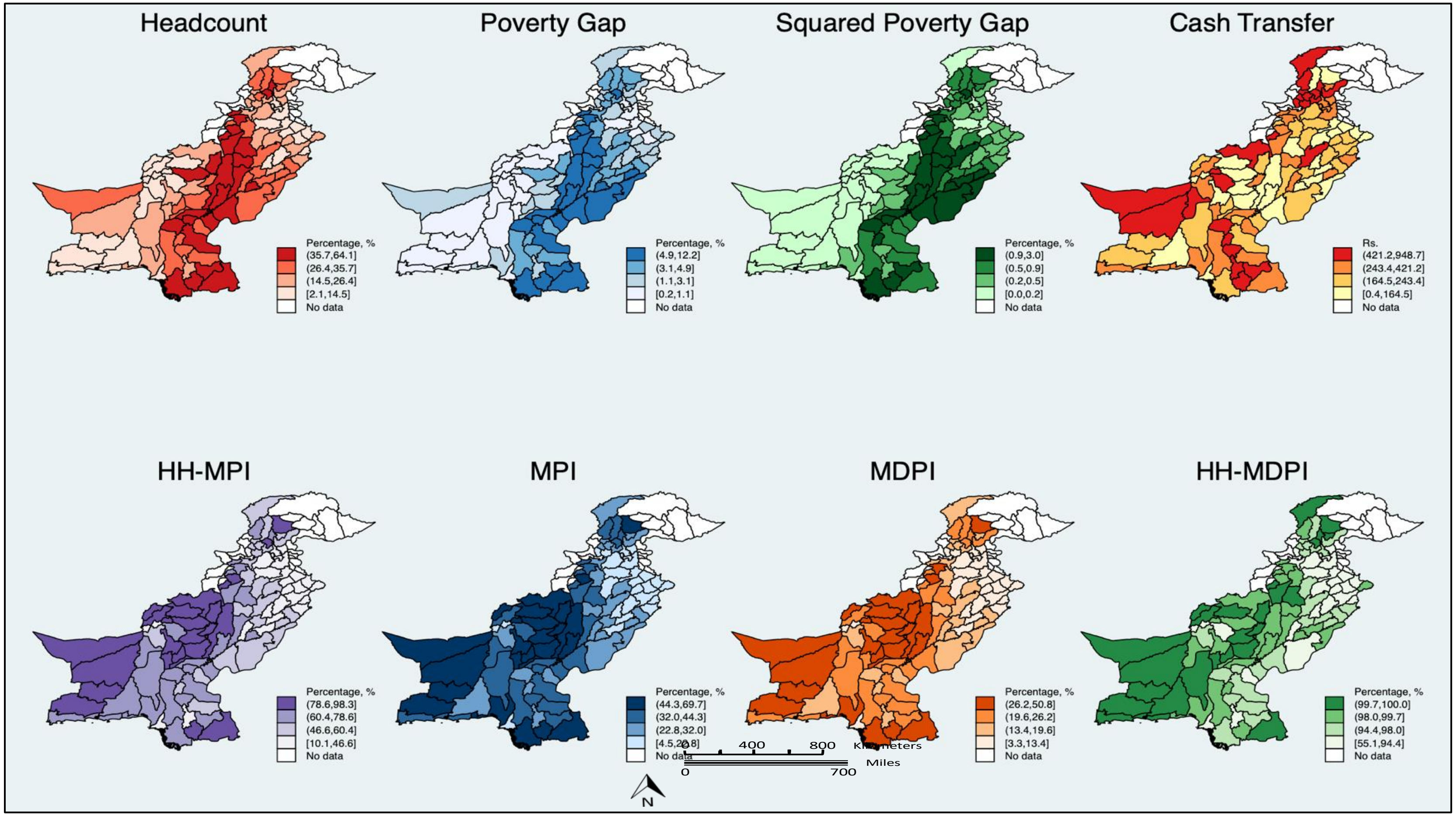
Appendix C

Figure C1 Poverty and Cash Transfer Mapping – 2008



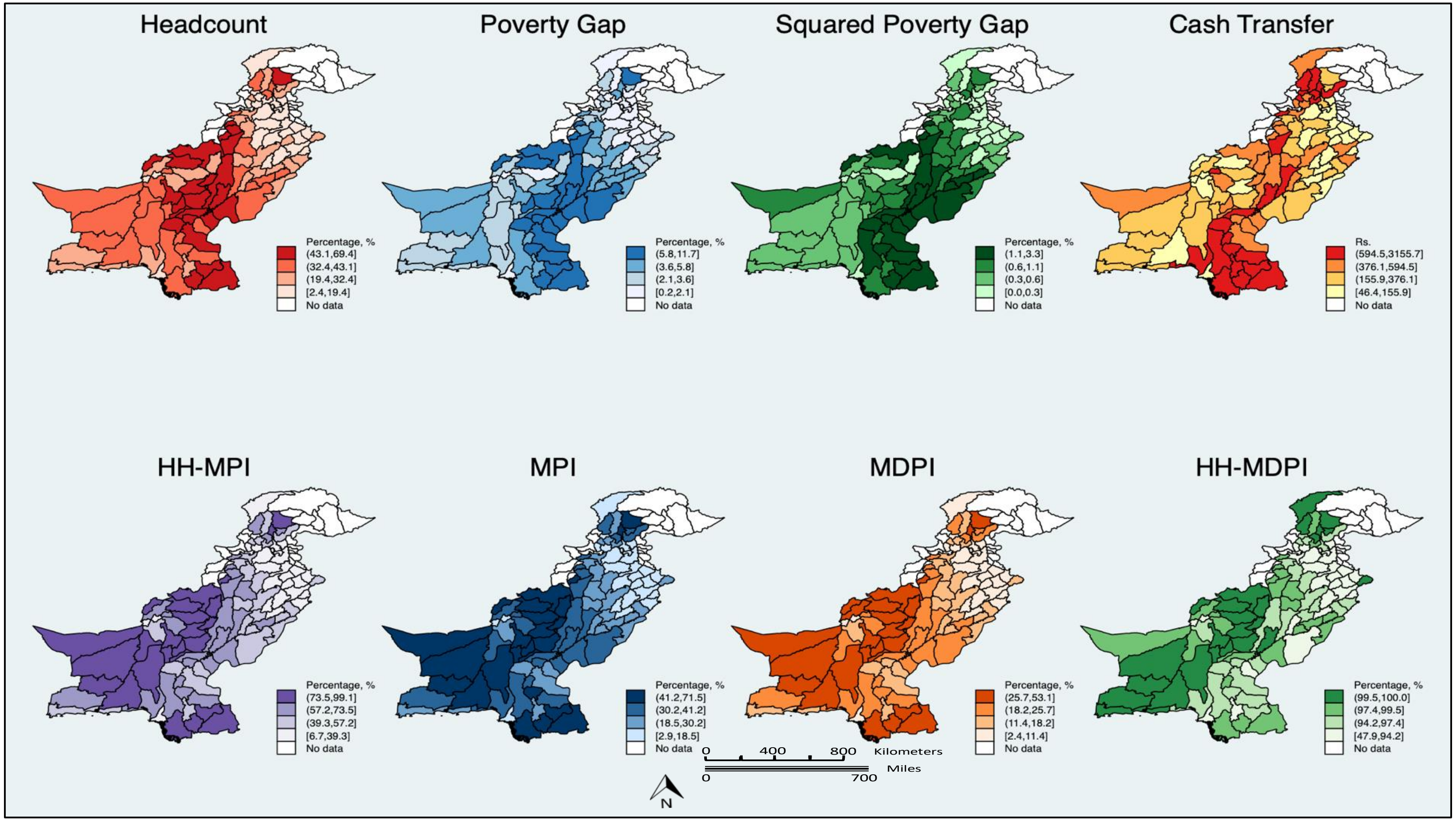
Notes: HH, Headcount Index; MPI-HH, Alkire & Foster (2011) Multidimensional Headcount Index; MDPI-HH, Multidimensional Distribution-sensitive Headcount Index; Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index; Cash Transfer (per capita) (BISP)

Figure C2 Poverty and Cash Transfer Mapping – 2010



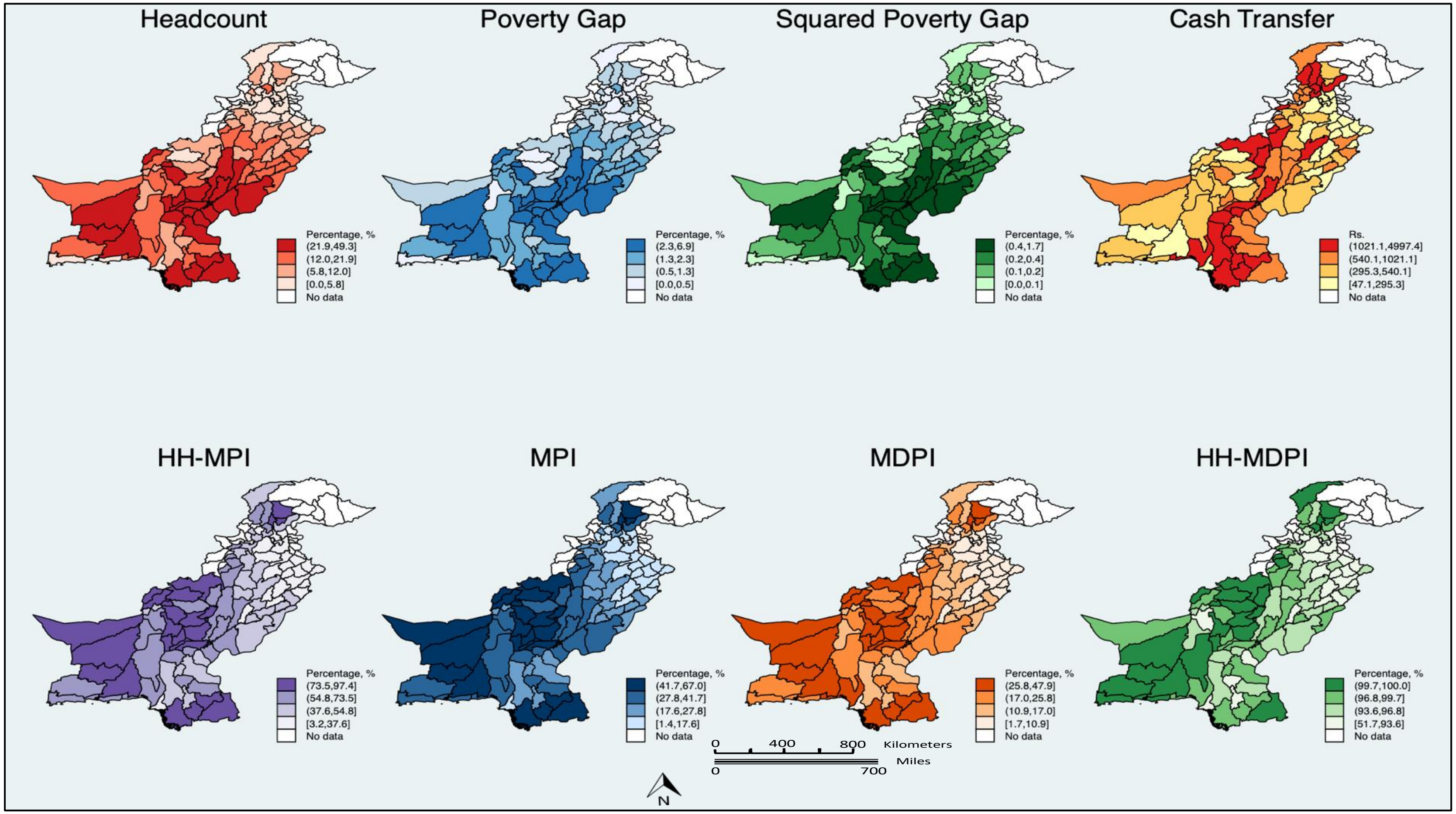
Notes: HH, Headcount Index; HH-MPI, Alkire & Foster (2011) Multidimensional Headcount Index; HH-MDPI, Multidimensional Distribution-sensitive Headcount Index; Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index; Cash Transfer (per capita) (BISP)

Figure C3 Poverty and Cash Transfer Mapping – 2012



Notes: HH, Headcount Index; HH-MPI, Alkire & Foster (2011) Multidimensional Headcount Index; HH-MDPI, Multidimensional Distribution-sensitive Headcount Index; Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index; Cash Transfer (per capita) (BISP

Figure C4 Poverty and Cash Transfer Mapping – 2014



Notes: HH, Headcount Index; HH-MPI, Alkire & Foster (2011) Multidimensional Headcount Index; HH-MDPI, Multidimensional Distribution-sensitive Headcount Index; Multidimensional Poverty Index with 33% cut-off; MDPI, Multidimensional Distribution Sensitive Poverty Index; Cash Transfer (per capita) (BISP)

Appendix D

Table D1: Blinder-Oaxaca Decomposition Headcount Index

Pre BISP	45.6*** (1.38)
Post BISP	33.2*** (1.18)
Difference	12.3*** (1.81)
Endowment	5.9** (3.02)
Coefficient	5.6*** (2.08)
Interaction	0.7 (3.19)

			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Young people < 15 years	210.5*** (47.75)	-23.1 (28.15)	-0.4 (0.52)	104.5*** (24.81)	4.3*** (1.39)
Adult people >35 & < 60 years	-102.9 (87.15)	-290.1*** (58.56)	3.1*** (0.82)	36.4* (20.45)	-2.02* (1.19)
Male headed Household	52.1 (32.91)	156.3*** (17.23)	-2.3*** (0.83)	-98.4*** (35.06)	1.5** (0.75)
High school in 30min return	3.4 (14.41)	-25.2** (13.75)	2.5* (1.44)	19.2 (13.41)	-2.8 (2.03)
Males	-3.6 (86.41)	-12.9 (49.97)	-0.04 (0.16)	4.7 (51.12)	0.03 (0.32)
Males who can read	2.11 (14.91)	-32.2*** (10.52)	1.48** (0.59)	22.6* (12.06)	-1.58* (0.92)
Hospital in 30 min return	-11.2 (14.48)	17.2 (13.25)	-1.6 (1.27)	-19.1 (13.16)	2.64 (1.89)
Own tractor	103.4** (42.68)	41.3 (30.25)	-0.1 (0.13)	2.23 (1.88)	-0.18 (0.22)
Own agriculture land	-2.8 (8.79)	12.5* (6.99)	1.07* (0.62)	-5.3 (3.87)	-1.3 (0.98)
Toilet facility	-1.2 (7.65)	-9.1* (4.90)	1.2* (0.69)	3.9 (4.56)	-1.06 (1.24)
Working population	-34.8** (17.97)	-106.4*** (10.14)	0.5 (0.77)	39.6*** (11.43)	-0.33 (0.52)
Own car	0.8 (32.86)	15.4 (20.30)	-0.15 (0.21)	-0.7 (1.94)	0.14 (0.38)
Concrete roof	0.7 (8.67)	5.5 (6.96)	0.4 (0.46)	-0.4 (0.88)	-0.31 (0.74)
More than 2 rooms	-6.8 (15.38)	-40.6*** (10.38)	-0.17 (0.36)	27.6* (15.17)	0.14 (0.31)
Child is immunized	-6.3 (8.04)	8.1 (13.99)	-1.45 (2.51)	-13.7 (15.37)	2.58 (2.89)
Education till 10th	-36.2*** (12.68)	-16.4* (9.62)	0.32 (0.24)	-10.2 (8.19)	0.39 (0.36)
Access to electricity	-2.3 (8.18)	17.4** (7.71)	1.58** (0.76)	13.3 (9.83)	-1.4 (1.06)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level

.

Table D2: Blinder-Oaxaca Decomposition Poverty Gap Index

Pre BISP	8.21*** (0.35)
Post BISP	5.36*** (0.27)
Difference	2.84*** (0.44)
Endowment	0.99*** (0.37)
Coefficient	1.72*** (0.45)
Interaction	0.13 (0.39)

			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Males	-5.3 (24.45)	15.78 (12.11)	0.05 (0.05)	-10.8 (13.98)	-0.07 (0.10)
Young people < 15 years	60.9* (33.49)	28.06 (18.72)	0.51 (0.36)	14.7 (17.17)	0.6 (0.72)
Youth people <35 & > 15 years	15.8 (40.28)	43.2** (21.66)	-0.07 (0.11)	-8.63 (14.43)	0.04 (0.10)
Adult people >35 & < 60 years	3.34 (43.79)	11.2 (23.88)	0.12 (0.26)	2.82 (9.71)	-0.16 (0.54)
Male headed Household	13.7 (8.99)	30.48*** (4.40)	-0.44*** (0.17)	-15.8* (9.45)	0.24 (0.17)
Males who can read	-1.4 (3.74)	-6.23** (2.46)	0.28** (0.13)	3.17 (2.96)	-0.22 (0.21)
Education till 10th	-7.5** (3.63)	-4.3** (2.36)	0.09 (0.06)	-1.62 (2.23)	0.06 (0.09)
Working population	-9.2* (4.88)	-28.2*** (2.49)	0.13 (0.20)	10.54*** (3.04)	-0.09 (0.14)
Own car	5.6 (9.37)	5.8 (5.10)	-0.06 (0.05)	-0.01 (0.53)	0.002 (0.10)
Access to gas	1.5 (2.60)	-3.97*** (1.46)	0.29** (0.13)	1.23* (0.67)	-0.39* (0.24)
Toilet facility	-0.69 (2.12)	0.96 (1.22)	-0.13 (0.17)	-0.83 (1.23)	0.22 (0.33)
High school in 30min return	2.09 (3.93)	-10.3*** (3.41)	1.00*** (0.39)	8.32** (3.51)	-1.2** (0.57)
Own tractor	41.6*** (11.61)	17.2** (7.28)	-0.05 (0.05)	0.87* (0.49)	-0.07 (0.07)
More than 2 rooms	-6.4* (3.61)	-9.7*** (2.39)	-0.04 (0.08)	2.64 (3.54)	0.013 (0.03)
Hospital in 30 min return	-4.8 (3.85)	7.5** (3.32)	-0.69** (0.34)	-8.29** (3.41)	1.15** (0.52)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table D3: Blinder-Oaxaca Decomposition Squared Poverty Gap Index

Pre BISP	2.07*** (0.11)
Post BISP	1.27*** (0.08)
Difference	0.79*** (0.13)
Endowment	0.28*** (0.10)
Coefficient	0.51*** (0.14)
Interaction	0.016 (0.12)

			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
	0.14	8.62**	0.03	-4.34	-0.03
Males	(7.06)	(3.69)	(0.02)	(4.08)	(0.03)
	-20.6***	-13.73***	0.15***	-1.34	0.07
Adult people >35 & <60 years	(5.17)	(2.95)	(0.04)	(1.16)	(0.06)
	6.35**	9.47***	-0.14***	-2.93	0.04
Male headed Household	(2.85)	(1.29)	(0.05)	(2.95)	(0.05)
	-0.52	-1.43**	0.14***	1.61*	-0.11
Males who can read	(1.19)	(0.76)	(0.05)	(0.94)	(0.07)
	-2.88**	0.28	0.03	-0.74	0.03
Education till 10th	(1.11)	(0.74)	(0.10)	(0.68)	(0.03)
	0.42	0.28	-0.002	0.007	-0.001
Own car	(2.84)	(1.13)	(0.01)	(0.16)	(0.03)
	10.6***	4.34***	-0.012	0.22	-0.018
Own tractor	(3.61)	(2.16)	(0.01)	(0.15)	(0.02)
	-1.99	-7.81***	0.04	3.22***	-0.03
Working population	(1.50)	(0.75)	(0.06)	(0.93)	(0.04)
	1.19	-2.97***	0.29**	2.8***	-0.41**
High school in 30min return	(1.30)	(1.04)	(0.11)	(1.12)	(0.18)
	0.44	0.003	-0.0003	0.22	-0.06
Toilet facility	(0.69)	(0.45)	(0.06)	(0.41)	(0.11)
	-1.24**	1.14***	-0.09*	-1.33***	0.19**
Concrete walls	(0.62)	(0.47)	(0.05)	(0.43)	(0.08)
	-0.09	-0.22	0.015	0.05	-0.008
Access to water in home	(0.60)	(0.30)	(0.02)	(0.26)	(0.05)
	-1.89	1.74*	-0.16	-2.43**	0.33**
Hospital in 30 min return	(1.21)	(1.02)	(0.10)	(1.06)	(0.16)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table D4: Blinder-Oaxaca Decomposition Multidimensional Poverty Index

Pre BISP	38.73*** (1.04)
Post BISP	31.7*** (0.79)
Difference	7.02*** (1.31)
Endowment	5.52*** (1.30)
Coefficient	0.81 (0.63)
Interaction	0.69 (0.57)

			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Males	60.8** (30.98)	15.3 (15.70)	0.048 (0.06)	23.3 (17.79)	0.14 (0.14)
Adult people >35 & <60 years	-99.4*** (22.70)	-79.6*** (12.47)	0.86*** (0.20)	-3.85 (5.04)	0.21 (0.28)
Males who can read	-24.5*** (4.93)	-34.4*** (3.23)	1.59*** (0.40)	6.58* (3.89)	-0.46 (0.29)
Education till 10th	-3.00 (4.57)	-7.49** (3.04)	0.15* (0.09)	2.31 (2.82)	-0.08 (0.11)
Male headed Household	28.8** (11.57)	9.93* (5.25)	-0.14 (0.09)	17.8 (11.99)	-0.27 (0.21)
Access to water in home	-2.99 (2.44)	-1.52 (1.17)	0.11 (0.09)	-0.57 (1.06)	0.10 (0.19)
Working population	-23.4*** (6.33)	-8.81*** (3.24)	0.04 (0.06)	-8.08** (3.93)	0.07 (0.11)
More than 2 rooms	-6.34 (5.18)	-3.93 (3.19)	-0.02 (0.04)	-1.97 (4.97)	-0.01 (0.03)
Hospital in 30 min return	-12.2** (4.99)	-14.23*** (4.18)	1.32*** (0.47)	1.36 (4.37)	-0.18 (0.61)
Concrete walls	-19.44*** (2.63)	-24.42*** (1.71)	1.97*** (0.66)	2.77 (1.75)	-0.4 (0.28)
Own tractor	7.92 (15.21)	1.14 (8.99)	-0.003 (0.03)	0.24 (0.63)	-0.019 (0.05)
Own agriculture land	0.97 (3.46)	-7.25*** (2.35)	-0.62*** (0.22)	2.83** (1.44)	0.7* (0.37)
High school in 30min return	0.49 (5.29)	0.65 (4.25)	-0.06 (0.42)	-0.11 (4.57)	0.01 (0.66)
Access to gas	-12.8*** (3.36)	-7.29*** (1.79)	0.53*** (0.18)	-1.25 (0.86)	0.4 (0.29)
Concrete roof	3.49 (3.02)	-3.73* (2.19)	-0.25* (0.15)	0.57** (0.30)	0.47* (0.26)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table D5: Blinder-Oaxaca Decomposition Multidimensional Distribution-Sensitive Poverty Index

Pre BISP	24.78*** (0.74)				
Post BISP	20.06*** (0.52)				
Difference	4.72*** (0.90)				
Endowment	2.58*** (0.82)				
Coefficient	1.13 (0.86)				
Interaction	1.00 (0.81)				
			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Males	42.57 (28.19)	-8.1 (12.95)	-0.02 (0.04)	25.94 (16.23)	0.16 (0.14)
Concrete roof	1.22 (2.75)	-4.63*** (1.81)	-0.31** (0.13)	0.46* (0.26)	0.39* (0.23)
Adult people >35 & <60 years	-80.27*** (19.33)	-48.7*** (10.21)	0.53*** (0.14)	-6.15 (4.25)	0.34 (0.24)
Male headed Household	26.6*** (10.51)	12.9*** (4.34)	-0.19** (0.09)	12.93 (10.73)	-0.19 (0.18)
Working population	-11.5** (5.54)	-2.96 (2.53)	0.014 (0.02)	-4.76 (3.37)	0.04 (0.07)
Education till 5th	-5.7 (9.94)	-4.84*** (1.52)	-0.26*** (0.08)	-0.74 (8.47)	-0.05 (0.54)
Education till 10th	-1.94 (5.31)	-8.86*** (2.54)	0.17* (0.09)	3.56 (3.03)	-0.14 (0.13)
Access to gas	-10.26*** (3.25)	-4.95*** (1.52)	0.36** (0.14)	-1.2 (0.81)	0.39 (0.28)
Access to water in home	-3.61 (2.28)	-2.95*** (0.96)	0.21** (0.08)	-0.26 (0.96)	0.05 (0.17)
High school in 30min return	-2.7 (4.74)	-2.42 (3.51)	0.24 (0.35)	-0.21 (3.96)	0.03 (0.58)
Concrete walls	-12.93*** (2.43)	-17.95*** (1.28)	1.44*** (0.48)	2.8* (1.54)	-0.40 (0.26)
Own tractor	2.34 (13.91)	2.22 (7.80)	-0.006 (0.02)	0.004 (0.57)	-0.0003 (0.04)
Hospital in 30 min return	-12.88*** (4.58)	-11.58*** (3.44)	1.08*** (0.38)	-0.87 (3.84)	0.12 (0.53)
Own agriculture land	-4.23 (2.82)	-9.14*** (1.82)	-0.78*** (0.20)	1.69 (1.16)	0.42 (0.29)
Own car	4.35 (11.28)	-10.35** (4.93)	0.100 (0.06)	0.74 (0.62)	-0.14 (0.13)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table D6: Blinder-Oaxaca Decomposition MPI Headcount Index

Pre BISP	68.29*** (1.45)
Post BISP	58.08*** (1.19)
Difference	10.21*** (1.88)
Endowment	8.04*** (1.89)
Coefficient	1.06 (0.77)
Interaction	1.10 (0.69)

			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Males	138.18*** (28.51)	69.69*** (22.46)	0.22 (0.16)	35.07* (18.59)	0.22 (0.18)
Young people <15 years	115.09*** (19.05)	64.8*** (14.44)	1.19*** (0.37)	22.5** (10.70)	0.92* (0.48)
Adult people >35 & <60 years	-58.89* (34.85)	-69.91** (28.22)	0.76** (0.33)	2.14 (8.73)	-0.12 (0.48)
Education till 10th	-4.48 (5.28)	-14.61*** (5.02)	0.28* (0.16)	5.21 (3.75)	-0.2 (0.17)
Working population	-11.62* (7.00)	-7.83 (5.23)	0.04 (0.06)	-2.1 (4.84)	0.02 (0.05)
Own tractor	16.46 (18.11)	34.9** (15.59)	-0.100 (0.09)	-0.66 (0.86)	0.05 (0.08)
Own agriculture land	-1.30 (3.89)	-10.62*** (3.90)	-0.91** (0.36)	3.2* (1.89)	0.79 (0.49)
Own car	-8.98 (14.38)	-20.26** (10.52)	0.19 (0.13)	0.57 (0.89)	-0.11 (0.18)
More than 2 rooms	-6.17 (6.12)	-19.45*** (5.31)	-0.08 (0.17)	10.8 (6.62)	0.05 (0.12)
Concrete roof	8.11** (3.55)	-0.44 (3.53)	-0.03 (0.23)	0.67* (0.40)	0.56 (0.35)
Hospital in 30 min return	2.59 (5.77)	-29.01*** (6.92)	2.69*** (0.84)	21.2*** (6.05)	-2.94*** (1.02)
High school in 30min return	-8.91 (5.83)	13.5* (7.12)	-1.33* (0.75)	-15.1** (6.20)	2.2** (1.00)
Access to water in home	-2.94 (2.85)	-3.6* (1.89)	0.26* (0.15)	0.28 (1.33)	-0.05 (0.24)
Access to gas	-30.58*** (4.13)	-18.55*** (3.07)	1.35*** (0.39)	-2.72** (1.17)	0.87** (0.43)
Concrete walls	-28.6*** (3.10)	-43.26*** (2.67)	3.49*** (1.16)	8.18*** (2.29)	-1.18** (0.51)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table D7: Blinder-Oaxaca Decomposition MDPI Headcount Index

Pre BISP	97.05*** (0.44)
Post BISP	95.01*** (0.41)
Difference	2.03*** (0.60)
Endowment	1.55*** (0.43)
Coefficient	0.42 (0.55)
Interaction	0.05 (0.36)

			Decomposition		
Variables	**Pre BISP**	**Post BISP**	**Endowment**	**Coefficient**	**Interaction**
Males	-1.03 (25.66)	-17.65 (17.78)	-0.05 (0.06)	8.51 (15.99)	0.05 (0.10)
Young people <15 years	97.12*** (12.93)	85.46*** (9.09)	1.57*** (0.39)	5.21 (7.07)	0.21 (0.29)
Adult people >35 & <60 years	16.9 (26.71)	-24.55 (20.50)	0.26 (0.22)	8.08 (6.55)	-0.45 (0.37)
Male headed Household	-10.68 (11.03)	7.25 (6.63)	-0.10 (0.10)	-16.93 (12.15)	0.26 (0.21)
Working population	7.36 (5.44)	0.23 (3.50)	-0.001 (0.02)	3.94 (3.58)	-0.03 (0.06)
Own tractor	36.63*** (13.77)	40.88*** (10.78)	-0.12 (0.11)	-0.15 (0.63)	0.012 (0.05)

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Appendix E

Table E1: Fixed-Effect Panel Regression: Headcount Index

Variables	Model 1	Model 2
Phase		40.82* (24.43)
Log Cash Transfer × Phase I		-2.16* (1.28)
Log Cash Transfers	-10.8*** (1.38)	-11.25*** (1.59)
Male headed Household	72.03*** (19.4)	64.16*** (19.86)
Males who can read	-36.2** (16.7)	-43.22*** (16.21)
Working population	-106.3*** (13.5)	-102.40*** (13.81)
Own agriculture land	-33.14*** (12.8)	-25.63** (12.89)
Access to gas	-61.4*** (12.1)	-66.71*** (12.00)
Access to electricity	-21.5* (12.7)	
High school in 30min return	-7.02 (6.8)	
R sq within	0.6327	0.6307
R sq between	0.3002	0.2805
R sq overall	0.3619	0.3535
Sigma_u	21.8	21.65
Sigma_e	13.8	13.81
Corr(u_i, Xb)	-0.7395	-0.7325
Prob F-stats	***	***

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E2: Fixed-Effect Panel Regression Poverty Gap Index

	Model 1	Model 2
Phase		18.70*** (6.15)
Log Cash Transfer × Phase I		-0.98*** (0.32)
Log Cash Transfers	-1.93*** (0.34)	-1.79*** (0.39)
Males	5.67 (14.5)	9.56 (14.40)
Male headed Household	8.8* (4.89)	6.48 (4.99)
Males who can read	-5.46 (4.15)	-4.83 (4.11)
Working population	-38.24*** (3.36)	-36.29*** (3.38)
Access to gas	-8.19*** (3.17)	-12.89*** (2.98)
Access to electricity	-11.7*** (2.98)	-8.42*** (3.19)
High school in 30min return	-10.51*** (3.14)	-2.70 (1.70)
R sq within	0.6375	0.6490
R sq between	0.1198	0.1242
R sq overall	0.2778	0.2799
Sigma_u	5.48	5.60
Sigma_e	3.40	3.36
Corr(u_i, Xb)	-0.7466	-0.7547
Prob F-stats	***	***

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E3: Fixed-Effect Panel Regression Squared Poverty Gap Index

	Model 1	Model 2
Phase		5.69*** (0.12)
Log Cash Transfer × Phase I		-0.30*** (0.09)
Log Cash Transfers	-0.49*** (0.101)	-0.44*** (0.12)
Males	2.56 (4.3)	3.73 (4.28)
Male headed Household	1.43 (1.45)	0.71 (1.48)
Males who can read	-1.13 (1.23)	-0.93 (1.22)
Working population	12.7*** (0.99)	-12.08*** (1.00)
Access to gas	-2.95*** (0.89)	-3.30*** (0.88)
Access to electricity	-3.61*** (0.93)	-2.97*** (0.95)
High school in 30min return	-1.09** (0.5)	-0.93* (0.50)
R sq within	0.6400	0.6519
R sq between	0.0339	0.0368
R sq overall	0.2321	0.2356
Sigma_u	1.67	1.69
Sigma_e	1.01	1.00
Corr(u_i, Xb)	-0.7443	-0.7496
Prob F-stats	***	***

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E4: Fixed-Effect Panel Regression Multidimensional Poverty Index

	Model 1	Model 2
Phase		-24.62*** (6.57)
Log Cash Transfer × Phase I		1.34*** (0.34)
Log Cash Transfers	-0.97*** (0.38)	-1.58*** (0.42)
Male	14.09 (14.7)	21.03 (15.00)
Adult people >35 & <60 years	-86.5*** (16.4)	-68.37*** (16.81)
Males who can read	-32.8*** (4.3)	-37.28*** (4.32)
Education till 10th	-11.12*** (2.98)	-15.08*** (3.04)
Access to water in home	-2.37** (1.26)	-
Working population	-9.62*** (3.51)	-12.73*** (3.67)
More than 2 rooms	-4.32 (4.45)	-10.42** (4.54)
Hospital in 30 min return	-9.22*** (1.75)	-
Own tractor	-9.06 (10.73)	-
Own agriculture land	-11.35*** (3.44)	-12.85*** (3.40)
Access to gas	-12.96*** (3.21)	-14.24*** (3.13)
Concrete roof	-3.46 (2.33)	-2.88 (2.39)
R sq within	0.5756	0.5557
R sq between	0.8084	0.6738
R sq overall	0.7742	0.6494
Sigma_u	8.21	9.72
Sigma_e	3.48	3.55
Corr(u_i, Xb)	0.5475	0.4185
Prob F-stats	***	***

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E5: Random-Effect Panel Regression Multidimension Distribution-sensitive Poverty Index

	Model 1	Model 2
Phase		-7.95 (6.10)
Log Cash Transfer × Phase I		0.35*** (0.32)
Log Cash Transfers	-0.82*** (0.26)	-1.21*** (0.27)
Concrete roof	-5.42*** (1.89)	-4.19** (1.95)
Adult people >35 & <60 years	-36.77** (15.76)	-36.13** (15.76)
Education till 10th	-7.47*** (2.57)	-8.32*** (2.60)
Males	31.16*** (11.64)	35.13*** (11.62)
Access to gas	-10.92*** (1.97)	-10.70*** (1.95)
High school in 30min return	-2.95 (3.51)	-2.48 (3.50)
Own car	-7.93 (5.92)	-8.66 (5.88)
Young people	40.83*** (7.32)	40.12*** (7.30)
Own agriculture land	-8.84*** (2.26)	-8.75*** (2.25)
Access to water in home	-0.59 (1.07)	-1.11 (1.19)
Hospital in 30 min return	-12.59*** (10.82)	13.58*** (3.38)
R sq within	0.4161	0.4167
R sq between	0.8192	0.8252
R sq overall	0.7642	0.7715
Sigma_u	3.13	3.03
Sigma_e	2.96	2.95
Corr(u_i, Xb)	RE	RE

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E6: Fixed-Effect Panel Regression MPI Headcount Index

	Model 1	Model 2
Phase		-31.47*** (8.52)
Log Cash Transfer × Phase I		1.79*** (0.45)
Log Cash Transfers	-0.96* (0.55)	-1.81** (0.55)
Male	49.61*** (19.66)	43.28** (19.60)
Youth people >15 & <35 years	-33.24*** (12.85)	-39.96*** (12.55)
Adult people >35 & <60 years	-80.57*** (22.0)	-81.72*** (21.99)
Male who can read	-31.07*** (5.9)	-36.77*** (5.69)
More than 2 rooms	-7.97 (5.96)	-12.27** (5.95)
Own car	-3.58 (12.2)	-
Education till 10th	-14.4*** (4.1)	-15.59*** (4.06)
Working population	-11.54*** (4.69)	-10.13** (4.66)
Access to water in home	-1.46 (1.76)	-
Own agriculture land	-12.47*** (4.69)	-15.09*** (4.60)
Access to toilet in home	-7.38*** (2.51)	-
Own tractor	-27.2* (15.7)	-27.48* (14.33)
Access to gas	-13.07*** (4.46)	-11.67** (4.39)
Hospital in 30 min return	-9.65*** (2.44)	-10.47*** (2.32)
Concrete walls	-17.47*** (6.1)	-
R sq within	0.5878	0.5889
R sq between	0.9124	0.7887
R sq overall	0.8853	0.7426
Sigma_u	9.16	14.67
Sigma_e	4.64	4.62
Corr(u_i, Xb)	0.6420	0.6287
Prob F-stats	***	***

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.

Table E7: Random-Effect Panel Regression MDPI Headcount Index

	Model 1	Model 2
Phase		-4.59 (3.44)
Log Cash Transfer × Phase I		0.26 (0.18)
Log Cash Transfers	-0.28* (0.16)	-0.19 (0.19)
Male	8.32 (7.68)	9.39 (7.64)
Education till 10th	-2.42 (1.60)	-4.59*** (1.57)
Adult people >35 & <60 years	-41.57*** (8.12)	-34.47*** (8.21)
Hospital in 30 min return	-3.39* (2.06)	-
High school in 30min return	-1.58 (2.10)	-
Own car	-27.61*** (3.99)	-20.99*** (3.96)
R sq within	0.1490	0.1790
R sq between	0.7198	0.6741
R sq overall	0.6323	0.5748
Sigma_u	3.93	3.83
Sigma_e	1.67	1.56
Corr(u_i, Xb)	RE	RE

Notes: Standard errors in () with ***, **, * denoting statistical significance at the 1%, 5% and 10% level.