# Evaluating Political Capture and Targeting Performance of The Benazir Income Support Program in Pakistan

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# Evaluating Political Capture and Targeting Performance of The Benazir Income Support Program in Pakistan

# Politieke toe-eigening en doeltreffendheid van het Benazir Income Support Program in Pakistan

Thesis

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*Dedication*

To my late grandmother, Heera Begum, whose lonely struggle put her children on the path of seeking education in hard times

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# Acronyms

| | |
|---|---|
| ADB | Asian Development Bank |
| AJK | Azad Jammu & Kashmir |
| ANP | Awami National Party |
| ATMs | Automatic Tellers Machines |
| BDCs | Benazir Debit Cards |
| BISP | Benazir Income Support Program |
| CBD | Community Based Development |
| CBT | Community Based Targeting |
| CNIC | Computerized National Identity Card |
| DFID | Department for International Development |
| ECP | Election Commission of Pakistan |
| EOBI | Employees' Old-age Benefit Institution |
| ESSI | Employees' Social Security Institution |
| FATA | Federally Administered Tribal Areas |
| FGDs | Focused Group Discussions |
| FMTF | Final Means Testing Formula |
| FSP | Food Support Program |
| HIES | Household Integrated Economic Survey |
| HVS | Household Vulnerability Survey |
| IVR | Interactive Voice Response |
| KP | Khyber Pakhtunkhwa |
| LFS | Labour Force Survey |
| LG | Local Government |
| LHWP | Lady Health Workers Program |
| LSMS | Living Standards Measurement Surveys |
| MIS | Management Information System |

| | |
|---|---|
| MNA | Member of National Assembly |
| MPA | Member of Provincial Assembly |
| MPI | Multidimensional Poverty Index |
| NADRA | National Database Registration Authority |
| NGO | Non-Governmental Organization |
| NICOP | National Identity Card for Overseas Pakistanis |
| NRSP | National Rural Support Program |
| NSER | National Socio-Economic Registry |
| NSPS | National Social Protection Strategy |
| OPM | Oxford Police Management |
| PBS | Pakistan Bureau of Statistics |
| PCO | Population Census Organization |
| PIN | Personal Identification Number |
| PML-N | Pakistan Muslim League-Noon |
| PMT | Proxy Means Test |
| POs | Partner Organizations |
| PPHS | Pakistan Panel Household Survey |
| PPP | Pakistan People Party |
| PRSPs | Poverty Reduction Strategy Papers |
| PSC | Poverty Score Card |
| PSLM | Pakistan Social and Living Standards Measurement (Survey) |
| PTI | Pakistan Tehrik Insaf |
| RDD | Regression Discontinuity Design |
| RSPN | Rural Support Network |
| SA | Social Assistance |
| SDGs | Sustainable Development Goals |
| SSNs | Social Safety Nets |
| TPE | Targeting Process Evaluation |
| UC | Union Council |
| UNDP | United Nation Development Program |
| USAID | United States Aid |
| WB | World Bank |

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# Abstract

This thesis evaluates political capture and targeting performance of the Benazir Income Support Program (BISP) under its two different targeting phases. BISP is a unique targeted social safety net program introduced in 2008-09 during an economic and financial crisis in Pakistan. Currently, BISP distributes Rs. 1,611 a month among targeted families. The female members of a poor family receive the transfer. The amount of the transfer is equal to approximately 20% of monthly income of an average daily wageworker and is equivalent to 10% of the government announced minimum wage for unskilled labour. BISP is the largest social safety net program in Pakistan's history and its coverage has increased from 1.76 million beneficiaries in 2008-09 to 5.63 million in 2017-18 and is expected to reach 7.7 million beneficiaries by the end of the fiscal year 2018-19. By using both primary and secondary data sources, this research tries to fill gaps in the evaluation of targeted programs in Pakistan. While the context and justification are set forth in the introductory chapter (chapter 1), the thesis answers the main questions in its three core essays.

The first essay (chapter 2) evaluates the targeting performance of the BISP program. It focuses on the BISP's initial targeting strategy, which relied on a decentralized method whereby parliamentarians and their political machines at the local level identified poor households. The essay uses household level data from Pakistan's Social and Living Standards Measurement (PSLM) Survey 2009-10. The overall reach of the program in terms of benefit incidence at the time of survey was 5.76% of the total population. While 10.4% of households in the lowest income quintile received the transfer with an odds ratio of 1.81, the benefit incidence in the richest income quintile was 1.7% with an odds ratio of 0.30. The results show that BISP benefits accrue mainly to the poorest three quintiles and

that the per capita annual income of BISP beneficiaries is substantially lower than that of non-recipient households. Households belonging to the poorest quintiles received the maximum share. The share declines as we move to the upper quintiles. Overall, 84% of program benefits go to the lowest three quintiles. While there is a divide in income levels across rural and urban areas of Pakistan, no significant differences in income levels were found in case of BISP recipient households. However, it should be noted that the poorest quintile in rural areas received a significantly higher proportion of benefits as compared to the same quintile in urban areas. This is probably because it is easier for community political leaders to differentiate between the poorest and poor in rural areas due to close community interactions and knowledge. Consistent with the existing literature, the results also show that in provinces where income inequality is higher, the distribution of BISP forms is more pro-poor.

The second essay (chapter 3) investigates the impact of political factors in explaining the distribution of BISP forms across different localities within a district. Using unique features of the BISP cash transfer program, the essay tries to explain variation in forms distribution as function of political power and influence. To explain political capture in the program, the essay combined three different data sets at locality level, which includes data on BISP forms distribution, census data on housing conditions and the 2008 voting patterns for the selected district. While anecdotal references to the possible capture of program benefits by local political elites abound, no systematic investigation is available. This essay conducts an in-depth analysis of the program by treating BISP forms as 'block grants' in the hands of politicians. The essay finds a very important role for political factors in explaining variation across localities in the forms distribution. Besides political factors, living in an urban locality increase chances of selection into the program as compared to living in a rural locality. Among the political factor, the most important explanatory factor is the presence or absence of an important politician in a locality. The definition of incumbent politicians for important politician is highly significant and explains most of the variation in forms distribution across localities. Other political variables such as voter turnout and whether a locality is swing or loyal also play a role in the explanation but not as big as important politician. Overall, normative considerations of efficiency and equity play no role as compared to political factors. Political factors drive the distribution of these grants in favour of politically strong localities. Importantly, the objective criteria imposed by the project design of the program does help in limiting spatial disparity in forms distribution by penalizing richer and politically powerful localities. The results suggests that, at least from the perspective of poverty reduction, discretionary powers over fund distribution needs to be curtailed or subject to additional rules based on some objective criteria.

The third essay (chapter 4) reports the results of an innovative survey conducted in 24 localities of one district where the government transfers BISP cash to the poor. The program's targeting efficiency was analysed and compared across two different targeting approaches. The first was a Community Based Targeting (CBT) process through politicians and the second, the use of a Poverty Score Card (PSC) to identify the poor. We hired and trained female enumerators to go inside houses and observe household characteristics as against the poverty scorecard census of the program, which observes households from a distance. The findings suggest that community targeting by local politicians does better than the poverty scorecard method in minimizing the exclusion of the poor when community perception of poverty is used. Similarly, the poverty scorecard method reduces the inclusion errors of non-poor into the program but at the cost of high exclusion errors of the poor from the program. Targeting based on relying on politicians to identify poor households has a higher correlation with the observations of enumerators and supervisors. The greater ability of local politicians over the poverty scorecard targeting method in identifying poor households may be attributed to the politician's use of local definitions and local knowledge about poverty. Moreover, the lack of rigor in the poverty scorecard census, its administration and built-in disadvantages in its design leads to higher exclusion errors. The results suggest that the poverty scorecard targeting of the poor may need to be accompanied by a parallel verification exercise, which relies on a community-based definition of poverty. Use of some categorical information (like illness or disability in a household, female-headed households, number of children in a household, high dependency ratios) about the households is also positively related to minimizing both inclusion and exclusion errors.

Chapter 5 provides concluding remarks on the overall thesis and its findings.

# Samenvatting

Dit proefschrift beschrijft de politieke toe-eigening van het Benazir Income Support Program (BISP, een uitkeringsstelsel) en de mate waarin de juiste doelgroepen worden bereikt met de twee verschillende strategieën van het programma. Het BISP is een uniek doelgroepgericht sociaal vangnetprogramma dat in 2008-2009 werd ingevoerd tijdens een economische en financiële crisis in Pakistan. Momenteel verdeelt het BISP 1611 Pakistaanse roepie per maand onder gezinnen die tot de doelgroep behoren. De vrouwelijke leden van een arm gezin ontvangen de uitkering. De uitkering bedraagt ongeveer 20% van het maandinkomen van een gemiddelde dagloner en komt overeen met 10% van het door de regering aangekondigde minimumloon voor ongeschoolde arbeid. Het BISP is het omvangrijkste sociale vangnetprogramma in de Pakistaanse geschiedenis en het aantal begunstigden is toegenomen van 1,76 miljoen in 2008-2009 tot 5,63 miljoen in 2017-18. Naar verwachting zal dit aantal verder stijgen naar 7,7 miljoen begunstigden tegen het einde van het belastingjaar 2018-19. In dit onderzoek worden zowel primaire als secundaire gegevensbronnen gebruikt om lacunes in de beoordeling van doelgroepgerichte programma's in Pakistan op te vullen. De achtergrond en motivering worden in het inleidende hoofdstuk (Hoofdstuk 1) uiteengezet en de belangrijkste onderzoeksvragen worden in drie centrale essays beantwoord.

Het eerste essay (Hoofdstuk 2) beschrijft in hoeverre het BISP-programma de juiste doelgroepen bereikt. Hierin wordt de aanvankelijke strategie van het BISP beoordeeld. Dit was een gedecentraliseerde methode waarbij parlementariërs met hun politieke machinerieën op lokaal niveau arme huishoudens aanwezen. Het essay is gebaseerd op gegevens over huishoudens uit *Pakistan's Living Standard Measurement (PSLM) Survey 2009-*

*2010* (een onderzoek naar de levensstandaard). In totaal werd 5,76% van de bevolking bereikt met het programma. In het laagste inkomenskwintiel ontving 10,4% van de huishoudens de uitkering met een odds ratio van 1,81, terwijl 1,7% van de huishoudens in het hoogste inkomenskwintiel de uitkering kreeg met een odds ratio van 0,30. Uit de resultaten blijkt dat vooral de armste drie kwintielen profiteren van het BISP en dat het jaarinkomen per hoofd van de bevolking van BISP-begunstigden aanzienlijk lager ligt dan dat van niet-begunstigde huishoudens. Huishoudens die behoren tot de armste kwintielen ontvingen het maximumaandeel. De hogere kwintielen kregen een kleiner aandeel. Over het geheel genomen ging 84% van de uitkeringen van het programma naar de laagste drie kwintielen. Hoewel er in Pakistan een verschil bestaat in inkomensniveau tussen stedelijke gebieden en het platteland, bleken er geen significante verschillen in inkomensniveau te zijn onder begunstigden van het BISP. Hierbij moet echter worden opgemerkt dat het armste kwintiel op het platteland een aanzienlijk groter deel van de uitkeringen ontving dan hetzelfde kwintiel in stedelijke gebieden. Dit ligt waarschijnlijk aan het feit dat lokale politieke leiders gemakkelijker onderscheid kunnen maken tussen de armsten en armen op het platteland gezien de nauwe onderlinge banden en goede kennis van de gemeenschap. De resultaten laten ook zien dat de verspreiding van BISP-formulieren meer ten goede komt aan de armen in provincies met een grotere inkomensongelijkheid. Dit is in overeenstemming met de bestaande literatuur.

Het tweede essay (Hoofdstuk 3) gaat in op de mate waarin politieke factoren de verspreiding van BISP-formulieren over verschillende plaatsen in een district kunnen verklaren. Aan de hand van unieke kenmerken van het BISP-uitkeringsprogramma wordt geprobeerd om de variatie in de verspreiding van formulieren als functie van politieke macht en invloed te verklaren. Om politieke toe-eigening van het programma te verklaren zijn drie verschillende datasets op plaatselijk niveau gecombineerd, waaronder gegevens over de verspreiding van BISP-formulieren, volkstellingsgegevens over huisvestingsomstandigheden en het stemgedrag in het geselecteerde district in 2008. Er doen weliswaar veel verhalen de ronde over de mogelijke toe-eigening van uitkeringen door de lokale politieke elite, maar er is geen systematisch bewijs. Dit essay beschrijft een diepgaand onderzoek naar het programma waarin BISP-formulieren worden behandeld als 'globale subsidies' in handen van politici. Politieke factoren blijken een zeer belangrijke rol te spelen bij het verklaren van de verschillen tussen plaatsen in de verdeling van de formulieren. Afgezien van politieke factoren maken inwoners van stedelijke gebieden meer kans op deelname aan het programma dan plattelandsbewoners. De belangrijkste verklarende politieke factor is of er al dan niet een belangrijke politicus aanwezig is in een plaats. De vraag of er onder de zittende politici belangrijke politici zijn is cruciaal en verklaart het grootste deel van de plaastselijke verschillen in de verdeling van formulieren. Andere politieke variabelen, zoals de opkomst bij verkiezingen en de vraag of plaatselijke kiezers loyaal zijn aan een bepaalde politieke partij zijn ook van invloed, maar in mindere mate dan de aan- of afwezigheid van een belangrijke politicus. Normatieve overwegingen van efficiëntie en billijkheid spelen in vergelijking met politieke factoren geen noemenswaardige rol. Politiek sterke plaatsen worden bevoordeeld bij de verdeling van de subsidies. Een belangrijk punt is dat de objectieve criteria die door de opzet van het programma worden voorgeschreven bijdragen aan de beperking van ongelijkheid tussen plaatsen, door rijkere en politiek machtige locaties te bestraffen. De resultaten wijzen erop dat, in ieder geval vanuit het perspectief van armoedebestrijding, de discretionaire bevoegdheid over de verdeling van de fondsen moet worden ingeperkt of aan bijkomende regels moet worden onderworpen op basis van enkele objectieve criteria.

Het derde essay (Hoofdstuk 4) beschrijft de resultaten van een innovatief onderzoek dat is uitgevoerd op 24 locaties in een district waar de overheid BISP-geld uitkeert aan de armen. De mate waarin het programma de juiste doelgroepen bereikt is onderzocht, waarbij twee verschillende benaderingen werden vergeleken. Bij de eerste benadering (*Community Based Targeting,* kortweg CBT) werden de doelgroepen aangewezen door politici. Bij de tweede benadering gebeurde dit met behulp van een *Poverty Score Card* (PSC; een scoreformulier om armoede vast te stellen). Speciaal daartoe opgeleide vrouwelijke onderzoeksmedewerkers voerden huisbezoeken uit en vergeleken de kenmerken van de bezochte huishoudens met de armoedegegevens die waren verzameld met het scoreformulier van het programma, waarbij huishoudens van een afstand worden geobserveerd. De resultaten geven aan dat CBT door lokale politici beter werkt dan de PSC-benadering om de uitsluiting van de armen tot een minimum te beperken. Ook met de PSC-benadering vermindert het aantal niet-behoeftigen dat in het programma wordt opgenomen, maar met deze benadering worden tevens veel behoeftigen onterecht uitgesloten van deelname. De methode waarbij politici de doelgroep van arme huishoudens aanwijzen levert hogere correlaties op met de waarnemingen van onze getrainde onderzoeksmedewerkers en toezichthouders. Het feit dat de methode waarbij politici arme huishoudens aanwijzen betere resutaten oplevert dan de PSC-methode kan worden toegeschreven aan het gebruik van lokale definities en lokale kennis over armoede door politici. Bovendien leidt de PSC-methode tot meer uitsluitingsfouten door onnauwkeurigheid en de nadelen van het ontwerp van deze methode. De resultaten wijzen erop dat de PSC-methode wellicht moet worden aangevuld met een parallelle verificatieprocedure die gebaseerd is op een definitie van armoede die past bij de betrokken gemeenschap. Het gebruik van bepaalde informatiecategorieën met betrekking tot huishoudens (zoals ziekte of handicap in een huishouden, een vrouwelijk gezinshoofd, het aantal kinderen in een huishouden, een hoge afhankelijkheidsratio) leidt ook tot minder gevallen van onterechte opname of uitsluiting.

Hoofdstuk 5 bevat afsluitende opmerkingen over het onderzoek in dit proefschrift.

# 1 Introduction

## 1.1 Statement of the Problem

There is an increasing global focus on social protection programs as the number of countries with Social Safety Nets (SSN)/Social Assistance (SA) has doubled in the last two decades from 72 to 149 countries, which mean that almost every developing country in the world has a set of SSN programs (World Bank 2017). For the first time, the provision of social protection is now part of the Sustainable Development Goals (SDGs). SDG 1 (Goal 1) calls for eradication of extreme poverty in all its forms by 2030 by asking governments to implement nationally appropriate social protection systems (Target 1.3) which can enhance the resilience of the poor and vulnerable (Target 1.5) in the face of extreme climate-related and other economic, social and environmental shocks. It also calls for significant mobilization of resources (Target 1.A) to end poverty in all its dimensions and to guarantee allocation of resources to direct (Indicator 1.A.1) and indirect (Indicator 1.A.2) poverty reduction efforts.[1]

In developing countries, there is a long history of relying on targeted interventions to combat poverty. Using updated data base of World Bank Atlas of Social Protection Indicators of Resilience and Equity (ASPIRE), Ivaschenko et al. (2018) examine trends in coverage, spending and program performance of SSN programs across the world in the third edition of The State of Social Safety Nets. Their review of programs in 142 countries suggests that commitment to SSN/SA programs has been growing over time, and that such programs are making a substantial contribution in the fight against poverty. They, however, noted that more needs to be done as program coverage and benefits are still very low and can achieve only a small reduction in poverty.

Countries across the world are constantly experimenting with different targeting methods to reach out to the poor and vulnerable. The most important question about these SSN programs is to learn what works in specific country contexts and circumstances in order to reduce poverty and vulnerability. Different targeted interventions use different strategies and methods to identify the poor in specific local contexts. To evaluate the impact of these SSN interventions, a stream of literature has evaluated targeting accuracy and the impact of these programs on poverty reduction.

The choice between different targeting methods is still an empirical question, as a large body of literature has not yielded a clearly superior approach. In this regard, the current thesis is an attempt to evaluate the targeting performance of an innovative program, Benazir Income Support Program (BISP), which has been operational in Pakistan since 2008. This chapter provides an overview of poverty, poverty reduction strategies, and available research on the BISP in order to place the BISP in its proper context. A brief overview of the available empirical literature on the BISP will help to identify gaps and develop the research questions for the thesis.

## 1.2 An Overview of Recent Poverty in Pakistan

According to the latest poverty figures released by the Government of Pakistan, 55 million people (6.8 million to 7.6 million households) of its total estimated population of 186.2 million, live below the poverty line (Government of Pakistan 2016).[2] Using consumption data from the Pakistan Social & Living Standards Measurement (PSLM) Survey for 2013-14, the poverty headcount ratio is 29.5 % of the total population, which means that approximately every third Pakistani lives below the poverty line. In monetary terms, the new poverty line stands at Rs 3,030 per adult equivalent per month. According to these new estimates, consumption-based poverty dropped from 57.9% in 1998-99 to 29.5% in 2013/14. In a recent study jointly published by UNDP Pakistan and Planning Commission of Pakistan, multidimensional poverty in Pakistan stands at 38.8% in 2014-15 as compared to 55.2% in 2004/05 (UNDP 2016a). Multidimensional Poverty Index (MPI) is a non-monetary measure of poverty based on the capability approach, which includes indicators on health, education and living standards. The average intensity of deprivation, according to the study, which reflects the share of deprivation experienced by every poor person on average, is 50.9%. According to the same report, the greatest contribution to multi-dimensional poverty on 15 indicators derives mainly from lack of years of schooling (29.7%) followed by lack of access to healthcare facilities (19.8%) and child school attendance (10.5%). Aggregated to three dimensions of multi-dimensional poverty, the greatest contribution to poverty stems from educational deprivation (42.8%), followed by living standards (31.5%) and healthcare (25.7%).[3]

While both consumption and multi-dimensional poverty have declined over time, inequality has risen. In 1987/88 the Gini coefficient, which measures income inequality, was 0.35; by 2013/14, it had risen to 0.41. Pakistan's richest 20 percent now consume seven times more than the poorest 20 percent (UNDP 2016b). In Pakistan, like in any other developing country, inequality traps are such that they reinforce each other. For instance (1) A majority of the sons of poor fathers remain poor and a majority of the sons of rich fathers remain rich; (2) The educational gap between rich and poor people is increasing; (3) Sons follow fathers in their choice of occupation; and (4) Girls are discriminated against in terms of educational expenditure and are concentrated in certain occupational niches (Burki et al. 2015). There are stark regional disparities; multi-dimensional poverty in rural areas is at 54.6% as compared to 9.3% in urban areas in 2014-15 (UNDP 2016a). Similarly consumption based poverty is 35.6% in rural areas as compared to 18.2% in urban areas (UNDP 2016a). There are sharp variations in poverty across provinces. From the perspective of multi-dimensional poverty, 31.5% of Punjab's population lives below the poverty line as compared to more than 70% of the population in the province of Balochistan and in the erstwhile Federally Administered Tribal Areas (FATA). Even within Punjab, poverty in 15 southern Punjab districts is much higher in comparison to 21 central and northern districts of Punjab. Within-district disparities in income and living standards across Pakistan can be seen by the increase in slum areas vis-a-via gated communities with barriers of division. The poor avail free and low-cost government hospitals and schools, which offer poor service delivery while the rich and middle-income class have opted out for the private providers of health and education services.

The need for a program like BISP was felt in the backdrop of the 2007-08 global financial crisis that hit Pakistan's vulnerable and poor population very deeply with double-digit inflation. To smoothen the adverse shocks of the financial crisis, fiscal allocations for social protection in Pakistan increased by seven-fold in 2008 (Gazdar 2011). As the financial crisis penetrated the real sector and trickled down to the household sector, it adversely affected poverty alleviation and the employment generation efforts of the government (Nasir 2011). According to Nasir (2011), the financial crisis hit the urban poor more than the rural poor and it created new poor due to loss of output and employment in many production sectors, especially those that were integrated with the world economy.

## 1.3 Social Protection in Pakistan & BISP as Main Social Protection Intervention

In 2007, prior to the introduction of the Benazir Income Support Program (BISP), the Government of Pakistan established a task force in the Planning Commission, which developed a comprehensive National Social Protection Strategy (NSPS) (Government of Pakistan 2007a). The document was an improvement over the earlier policy work done under different Poverty Reduction Strategy Papers (PRSPs) beginning in 2003. In a major departure from the PRSPs, which mainly focused on the broad category of poverty reducing budgetary expenditures, the NSPS focused on providing direct benefits to the poor and vulnerable. There was a tendency under PRSPs to inflate pro-poor expenditure by including non-targeted consumer subsidies and other expenditures such as expenditure on higher education, large-scale infrastructure projects of roads (Nasim 2012). Nasim (2012) observes that in 2007-08, a year before the introduction of the BISP, 'pro-poor expenditure' or expenditures on safety nets, was 24 times higher than in 2000-01 largely as a result of the inclusion of a range of non-targeted consumer subsidies, including expenditures on law and order and microfinance. To overcome such anomalies and to define the parameters of social protection, protecting the poor and vulnerable was thus considered as the main pillar under the new National Social Protection Strategy (NSPS). These policy documents under NSPS reviewed the existing cash and other transfer programs in the country and concluded that there were serious gaps in targeting mechanisms, and the reach and design of the various programs. According to these review studies, social protection programs were inadequate and did not reach the poorest of the poor. Multiple factors were identified in various research works as contributors to the weak performance of safety net programs in Pakistan. These included, the prevalence of small, fragmented and duplicative programs; low spending levels resulting in insufficient coverage and low benefit adequacy; governance challenges resulting in infrequent and irregular payments to beneficiaries; lack of transparent eligibility criteria; political interference and corruption; and poor monitoring (Gazdar 2011, Government of Pakistan 2007a, Jamal 2010, DFID 2005, Heltberg et al. 2007, Government of Pakistan 2007b, World Bank 2013, ShuHong and Ranjha 2017).

Pakistan was in the grip of serious political and economic turmoil during 2007 and 2008, which culminated in the election of a new government and the exit of direct military rule after a decade. Soon after assuming office, a federal coalition government headed by Pakistan People's Party (PPP) announced the launch of the BISP program. In its first federal budget presented to the parliament barely 10 weeks after forming a government, an amount of Rs. 34 billion was allocated for the BISP program (Gazdar 2011). To compete with Pakistan People's Party (PPP)at the centre, the Pakistan Muslim League-N (PML-N) also launched its own pro-poor program in the country's biggest province, Punjab. Punjab's provincial government announced a Food Support Program (FSP) and a subsidized bread (Sasti Roti) scheme with a total outlay of Rs. 22 billion (Nasim 2012).

The Benazir Income Support Program (BISP) was launched in July 2008 with the immediate objectives of consumption smoothing and cushioning the negative effects of food crisis and inflation on the poor, particularly women, through the provision of cash transfers. Initially, a sum of Rs 1,000 per month was given to a female member of an eligible household. The monthly instalments were later enhanced to Rs. 1,200 per month (1st July, 2013), and then to Rs. 1,500 per month (1st July, 2014) and then further increased to Rs. 1,567 (1st July, 2015). Currently, the monthly instalment to beneficiary families is Rs. 1,611. The amount of the transfer is equal to approximately 20% of the monthly income of an average daily wage worker and is equivalent to 10% of the government announced minimum wage for unskilled labour. As households in low income brackets in Pakistan spend a larger portion of their income on food (Haq and Zia 2009), this cash transfer enables beneficiary households to meet their dietary requirements. For example, at the initiation of BISP in 2008, Rs. 1,000 a month would have been sufficient to finance the flour consumption of a 5-6 member family for 20-25 days. Some policymakers and commentators in Pakistani press showed their concerns that continued receipts of cash transfers may reduce labour supply and thus may affect production. These concerns were unfounded as recent empirical work by Ambler and de Brauw (2019) on BISP shows. They found no impact of the BISP grant on household aggregate labour supply. When they break up estimates by gender, they found little evidence of a change in female labour supply, strong evidence of male labour supply, and no evidence of changes to child labour. This stereotype about negative impact of cash transfer programs is also being debunked elsewhere in the world. Analysing data from seven randomized control trials of government-run cash transfer programs in six developing countries throughout the world, Banerjee et al. (2017) find no systematic evidence that cash transfer programs discourage work.

BISP is the largest social safety net program in Pakistan's history and its coverage has increased from 1.76 million beneficiaries in 2008-09 to 5.63 million in 2017-18. It is expected to reach 7.7 million beneficiaries by the end of fiscal year 2018-19. Similarly, the total amount transferred to beneficiaries increased from Rs. 15.32 billion in 2008-09 to Rs. 125 billion in 2018-19 (Table 1.1). The program is being implemented in all four provinces (Punjab, Sindh, Baluchistan and Khyber-Pukhtunkhwa) including erstwhile Federally Administered Tribal Areas (FATA), Azad Jammu and Kashmir (AJK) and Islamabad Capital Territory (ICT). Besides cash transfer, the program also has other components such as Waseela-i-Sihat (health insurance), Waseela-i-Rozgar (Vocational and technical training for employment generation), Waseela-i-Haq (extension of small loans for starting a business) and financial assistance for those who are hit by recent floods, bomb blast victims, Internally Displaced People (IDPs) due to conflicts in parts of Pakistan. Qualification requirement for these components is the same as that for the cash transfer component. The current government of Pakistan formed by the Pakistan Tehrik e Insaf (PTI) party has added some additional dimensions to the program, which will be implemented in the coming days and months. It is pertinent to note that both Pakistan Muslim League-Nawaz (PML-N) and PTI government tried to rename the program at the start of their government but they both faced strong backlash from the Pakistan People Party (PPP), civil society, intelligentsia and mainstream media. The program is named after the martyred political leader Benazir Bhutto of PPP who lost her life in a terrorist incident in December 2007.

Since its inception, the BISP has gone through two major phases of transition. In the initial phase of BISP (2008-09 to 2010-11), beneficiaries were identified by elected parliamentarians (and their political machines) and cash transfers were delivered to eligible families by postal workers of the Pakistan Postal Services. In 2010-11, on the recommendation of the World Bank and with its technical assistance, the identification of beneficiaries for the program benefit was switched to a Poverty Score Card (PSC) approach. A household's poverty score based on household demographics, assets, and other measurable socio-economic characteristics was created. In this 2nd phase of the program, around 97% of the beneficiary households received cash payments through smart card ATMs issued by commercial banks.[4]

During the initial phase, in July 2008, no reliable data was available to identify poor and vulnerable households. To overcome this constraint, parliamentarians were entrusted with the task of identification of the underprivileged and vulnerable households. All parliamentarians, irrespective of party affiliation, were provided with an equal opportunity to recommend eligible households. Members of the National Assembly and the Senate were given 8,000 BISP application forms each, while members of provincial parliaments were given 1,000 forms each. There were a total of 1,174 parliamentarians in Pakistan at the time, consisting of 104 Senators, 342 members of National Assembly and 728 members of four provincial assemblies. They were supposed to distribute BISP forms to households which they considered poor with broad guidelines given to them by the program management. To identify these households the Federal government developed a 13 point criteria which the parliamentarians were to follow.[5] The forms received from Parliamentarians were verified through the National Database and Registration Authority's (NADRA) database and out of 4.2 million forms received from Parliamentarians, 2.2 million families were found eligible for cash transfers. This phase of BISP targeting through politicians can be termed as community-based identification of beneficiaries where parliamentarians used their political machines to distribute the forms in their constituencies.

In this first phase, the BISP program had a hybrid design with features of formulae based grant program at the district level with centrally mandated and locally administered decentralized non-formulae based beneficiary identification. To reach the poor, there were three tiers of verification of the poverty status of BISP applicants. In the first tier, a political party member of the national or provincial assembly distributed the BISP forms in their constituency through their party office, political activists or in their individual capacity. Political parties have organizational set ups at the levels of District, Sub-district and Union Councils (municipality). Union Councils (UC) are the lowest level in the administration of each district, which on average contains 2-3 localities. Each district is divided administratively into different UC where each parliamentarian has a party organization, which may or may not be active. These forms reach political activists at the union council through their party organization or parliamentarian. There were no specific criteria about how many forms should be distributed in each UC or locality thus forms distribution entirely left to the discretion of the parliamentarians. At the UC level, the forms were distributed as per the local knowledge of the political workers there.

The second tier of selection into the program relied on the verification of the details of the applicants by the members of the local UC. Households had to fill in their particulars in the BISP form and return them to the elected members of the UC for approval. Each UC at the time had an elected assembly consisting of 13 members. The completed application form had to be signed by any elected member of the UC. At this layer of verification, it was not likely that a member of UC would reject the applicant's eligibility. However, the process encouraged self-selection, as the various layers of verification created social stigma for rich households who would have to lie to receive a meagre amount of Rs 1,000. Due to the connections of the elected UC members, it was very likely that such gossip about rich households applying for BISP would spread quickly. This social stigma was expected to discourage rich households from applying to the program. Another element which was incorporated in the application form was the oath that the information provided in the application form was correct and that any misinformation by the applicant may deem the household ineligible for the program benefits. For some people with religious leanings, this can be a possible reason not to apply for the program if they see themselves as non-eligible.

In the third tier of selection into the program, National Database and Registration Authority (NADRA) was to verify the eligibility of the applicants based on the specified objective part of the ineligibility criteria (See Appendix I). When completed forms, verified both by member of the UC and member of the parliament, reached the BISP head office, they were delivered to NADRA. NADRA has a management information system

 

(MIS) where any citizen who is registered with NADRA has a Computerized National Identity Card (CNIC). NADRA can verify the following information regarding each registered citizen:

a. Government or semi-government servant or pensioner.
b. Holder of Machine Readable Passport (MRP)
c. Holder of a bank account in any foreign bank
d. Holder of National Identity Card for Overseas Pakistanis (NICOP)
e. Number of members in a family

A final list was prepared by NADRA that divided the applicants into, eligible, ineligible and withheld applicants. BISP rejected application forms as prescribed by the ineligibility criteria of the program. Withheld forms were those forms which have discrepancies such as duplication of forms, not accompanied by relevant documents, signatures and CNIC number. So by the very design of the program, there might have been variations in targeting of the program due to heterogeneity of different parliamentarians and their associated political activists. Moreover, there was no geographical targeting of the program so areas with different prevalence of poverty received the same number of forms, which may lead to different targeting performance in different regions. Some political parties boycotted the election of 2008 and it could be argued that in the strongholds of these political parties, the elected representatives might not be the 'true' representatives of the people. Such representatives may thus be not under the same political pressure as of those who are truly representing the people, which may lead to differential targeting outcome. There was also no restriction on the parliamentarians to distribute forms only in their own constituencies, which may have induced some parliamentarians to distribute forms unequally across different regions and localities within his or her constituency.

A website was created for the program where individual applications and benefit payment status could be tracked.[6] Parliamentarians were given unique usernames and passwords to track the status of applicants of their constituency, while they could also check the original scanned application forms. Majority households targeted through the program had little or no access to the internet, thus, they submitted their grievances through their parliamentarians. However, as I noticed in my fieldwork, people in remote areas of district Swabi usually came to city centres to visit internet cafes to track their eligibility and cash amounts. The internet cafes usually charged an amount of Rs 20 to inform the applicant about their eligibility, funds transfer, and money-order number.

In the second phase of the BISP project, the Government of Pakistan decided to move from politicians' targeting to Poverty Score Card (PSC) targeting. With technical assistance from the World Bank in 2010-11, the BISP project office carried out a countrywide poverty census to collect information on various socio-economic and demographic characteristics of the households. BISP office developed a Poverty Score Card (PSC) using the 2005-06 Pakistan Social and Living Standards Measurement (PSLM) Survey, which was later updated to 2007-08 PSLM survey. The PSC is based on 23 variables and uses poverty characteristics of the households that include, among other variables, household size, type of housing and toilet facilities, educational status of children, household assets, agricultural landholding, and livestock ownership (See appendix II for all the indictors). The nationwide poverty scorecard census enabled the BISP project office to identify eligible households. The poverty score lies between 0 and 100 and a score is calculated for each household. This was an effort to identify poor households through a multi-dimensional measure. The census was started in October 2010 and was completed across Pakistan except in two regions of Federally Administered Tribal Areas (FATA) where the security situation was volatile. Around 27 million households were reached through this census where 7.7 million households were identified living below a cut-off score of 16.17. Out of 7.7 million households, 5.6 million households were reached through cash transfers as of June 2016.[7]

In the case of the BISP, the World Bank team in collaboration with the BISP office examined 99 different models before settling on a Final Means Testing Formula (PMTF) (World Bank 2009b). The final formula included 23 variables, which were identified through regression analysis based on the PSLM data set. All the coefficients were statistically significant at the 5 percent level and the R-Square of the model was more than 55 percent. According to World Bank simulations, the targeting performance rate (coverage, under coverage & leakage) improves as the target group shifts from the poorest 10% percent to the poorest 30%. Currently the BISP program administration claims to have reached 5.6 million households as on end-June 2016 from among the 27 million households surveyed, which roughly covers 19.6% of the total households. According to the World

Bank simulation for the BISP poverty scorecard, if the poorest 20% of the population is set as the target group (close to the current 19.6% coverage), the under-coverage rate is 61% and the leakage rate is 40% while the coverage rate is 13%. This means 61% of the poor (the poorest 20% of the population) will be excluded while 40% of beneficiaries are non-poor (or do not belong to the poorest 20% of target population) (World Bank 2009b). The literature available on the simulations studies of targeting performance of World Bank poverty score cards across the developing world ascribe these high exclusion and inclusion errors to the in-built design errors and low explanatory power of the regressions which associate household characteristics with poverty.

The BISP's poverty scorecard census used for calculations of the poverty score serves as a rich information resource base on poverty. The BISP database is used by both federal and provincial governments for many other interventions to target the poor and their vulnerabilities. The federal government and the provincial governments of Punjab and Khyber Pakhtunkhwa are using BISP poverty lists to target their respective health insurance schemes. The federal government launched a health insurance scheme under which 4.6 million families would be provided with health insurance in 34 districts of the country, which will be scaled up later on.[8] [9] Similarly, the provincial government of Khyber Pakhtunkhwa launched a health insurance card to ambitiously cover 1.8 million households through which eight individuals per household are entitled to free medical treatment up to a maximum of Rs 54,000.[10] Similarly, in the absence of a regular census in Pakistan since 1998, researchers have been using the BISP census database to find different correlates of household characteristics for better understanding of social indicators (Arif 2015). In cases of natural disasters and conflict, BISP poverty lists are used to reach out to the poorest of the poor amongst those affected. A fresh pilot survey of BISP was started in June 2016 as, according to the program administration, many changes have taken place since the last survey in 2010-11[11]. The current government of PTI have resolved to complete the updating of the National Socio-Economic Registry (NSER) so that entry and exit into the program can be based on the updated poverty scorecard for the program.[12]

According to Gazdar (2011), the continued commitment of different governments to the fiscal outlay for the BISP (See Table 1.1), the enhanced program scale with linking of other programs to BISP, a database of 27 million households' socio-economic profile, and primary focus on women beneficiaries has truly been an irreversible paradigm shift. Moreover, the BISP program has received substantial technical and financial assistance from international donors like the World Bank, the Asian Development Bank, USAID, DFID and other development institutions over the years.

***Table 1.1***
*Yearly BISP Grants and number of Beneficiaries*

| *Fiscal Years* | *Total Yearly Releases (Rs in Billion)* | *Funds Transferred to Cash Grants (Rs in 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 | 15.85 | 1.3% | 0.10% | 1.76 | Phase I | 1,000 |
| 2009-10 | 39.94 | 34.83 | 3.0% | 0.19% | 2.58 | Phase I | 1,000 |
| 2010-11 | 34.42 | 34.96 | 2.2% | 0.19% | 3.10 | Phase I | 1,000 |
| 2011-12 | 49.53 | 45.88 | 2.6% | 0.25% | 3.68 | Phase I & II | 1,000 |
| 2012-13 | 50.10 | 46.47 | 2.6% | 0.22% | 3.75 | Phase II | 1,000 |
| 2013-14 | 69.62 | 66.31 | 3.1% | 0.28% | 4.64 | Phase II | 1,200 |
| 2014-15 | 91.78 | 89.04 | 3.5% | 0.33% | 5.05 | Phase II | 1,500 |
| 2015-16 | 102.00 | 98.53 | 3.3% | 0.35% | 5.21 | Phase II | 1,567 |
| 2016-17 | 111.50 | 104.37 | 3.3% | 0.35% | 5.46 | Phase II | 1,611 |
| 2017-18* | 121.00 | NA | 3.0% | 0.35% | 5.63 | Phase II | 1,611 |
| 2018-19* | 125.00 | NA | 3.0% | 0.35% | 7.70 | Phase II | 1,611 |

Source: Economic Survey of Pakistan 2017-18[13]
*Figures for the year 2017-18 & 2018-19 are budget projections.
** Phase I of project was targeting of program through parliamentarians while Phase II of the project was targeting through Poverty Score Card

## 1.4 Distribution Mechanism of BISP Benefits[14]

The BISP experimented with different payments distribution mechanisms for the cash grants to reach the beneficiaries. Initially BISP distributed its funds only through Pakistan Post using money orders delivered by postmen at the doorstep of the beneficiaries. Pakistan Post has a network of 12,340 post offices across the country, and in some areas, Pakistan Post has incorporated local shopkeepers to act as local postmen. Since the inception of BISP, a total of Rs. 132.5 billion has been distributed through Pakistan Post.

The government aimed to have a transparent mechanism of cash distribution to the eligible beneficiaries, which guaranteed separation between recipient selection and benefits disbursement. The disbursement mechanism was designed in such a way that there was minimum intermediary involvement or human interaction in the process of transmission of funds from the Treasury to the recipient. Neither the program management nor parliamentarians had any control over or access to funds, which were transferred electronically from the Treasury to the Pakistan Post and then disbursed electronically to BISP recipients. In fact, the first time actual cash comes into play is when postmen deliver the amount to the designated female head of the family. The recipient of the cash transfer has to sign a document or provide a thumb impression on the money order which is then transmitted to the BISP administration. However, while doing my survey in District Swabi, I found a number of anomalies on the part of distribution of funds among the beneficiaries. In some localities, politicians did collude with postmen to appropriate funds at the expense of poor families. Some postmen were taking a fixed amount of money from the funds as their 'due right' while delivering the money. Some even went to the extent of pocketing the entire amount while pretending to the beneficiaries that their funds had not been transferred, or that their funds had been stopped due to some unknown reasons. There were also plenty of cases where poor women gave money to the postmen 'voluntarily'.

Due to these complaints, the BISP experimented with other payments systems. In 2010, they introduced a Smart Card payment mechanism, an Automatic Teller Machine (ATM) type card, which allows the beneficiaries to collect their transfer instalments from different franchises. These franchises were authorized by BISP and provided with the required cash for payment to the beneficiaries. The beneficiary was required to collect the payment personally from the franchise on identification through her CNIC. A total of Rs. 12.9 billion has been disbursed through these Smart Cards.

Another method introduced in December 2010 was through mobile banking where beneficiaries were provided with a mobile set and a SIM card. The beneficiaries were informed of the availability of payments by an Interactive Voice Response (IVR) service. The payment was then collected from a franchise using a Personal Identification Number (PIN) that was sent via text message. The beneficiary was required to collect the payment personally from the franchise on identification through her CNIC. The beneficiary also signed a receipt. A total of Rs. 10.0 billion has been disbursed through mobile money. In February 2010, another major shift in payment system was made where payments to beneficiaries were made through Benazir Debit Cards (BDCs). This mode of payment was based on an ATM card, which allowed the beneficiary to withdraw payment instalments through the ATM of a bank authorized by BISP. This is the latest mode of payment and is being introduced in all districts. So far, a total of Rs 256.7 billion has been distributed far through this method. Most recently, from 2015-16, BISP is trying to shift to another secure method for payments to beneficiaries which is called a biometric verification system. The process of shift is still going on and so far, a total of Rs 245.6 billion has been distributed through this system.

## 1.5 An Overview of Existing Empirical Literature on BISP

This section reviews the existing empirical literature on different aspects of the BISP program and highlights gaps in the literature. With the exception of a series of impact evaluation studies conducted by Oxford Policy Management (OPM), empirical literature on evaluating different aspects of BISP program is scarce and lacks rigor. Most of the existing literature on BISP focuses on its targeting effectiveness, its gender and women empowerment dimension, its impact on poverty reduction and mitigating negative effects of shocks to the households. A few studies, like those conducted by OPM are comprehensive, rigorous and focus on multiple aspects of the BISP program. OPM studies were specifically sanctioned by the BISP program office with the purpose of feeding into ongoing programme operations. Before discussing OPM studies later in this section, we will first review independent studies on BISP.

A few studies have been conducted to empirically evaluate the targeting performance of the BISP program. The first ever evaluation was conducted by the World Bank in 2009 in its rapid assessment of the BISP's targeting process of both phases of the project (World Bank 2009). The study was conducted in 15 randomly selected districts and relied on a sample of 2,500 households. The study found that beneficiary identification by parliamentarians was pro-poor as around 65% of the total benefits went to the poorest 40% of the population. The study further found that targeting through poverty scorecard did better compared to parliamentarians' targeting as over 75% of benefits reached 40% of the population under the PSC method. The study, however, concluded that the poverty scorecard method is not a very good instrument for identifying the poor because it considers a limited set of characteristics and may not include other characteristics considered by parliamentarians. For instance, households considered ineligible based on their poverty score might have been assessed as eligible by the parliamentarians because they may have considered a disabled/seriously ill person or the fact that a family might be headed by a woman. This is true as a former chairperson of BISP wrote in her book that 35% of BISP recipient households, targeted in the 1st phase of the program by parliamentarians, were headed by females as opposed to only 9% of overall households in the 2007-08 household survey (Memon 2018). She also noted that parliamentarian-based beneficiary identification has clearly prioritized female-headed households and those households, which had a seriously disabled or ill person. On the other hand, she found that political connectedness of the beneficiary households does influence allocation of resources during political targeting phase but this does not necessarily signal corruption. Another study of targeting efficiency, Farooq (2014), found that BISP recipients were mostly poor. Using three rounds (2001, 2004 & 2010) of data from the Pakistan Panel Household Survey (PPHS) conducted in 16 districts, the author classified households into 3 categories of 'received', 'attempted' and 'never attempted' and found that both categories of 'received' and 'attempted' were poor. This was the time when the Poverty Score Card method had not yet been initiated. Based on key informant interviews, Khan and Qutub (2010) report that during the BISP politicians' targeting phase, benefits went mainly to the poor but with a large under coverage rate. In an appraisal of social protection programs in Pakistan, Jamal (2010) recommends the use of the proxy means test (PMT) to policy makers to select and identify beneficiaries but fails to base this on any rigorous data evaluation of his own or other research work.

Numerous other studies have focused on the gender dimension of the BISP initiative as cash is going to households in the name of a female member, which may influence intra-household gender relations. Using data from Pakistan, Hou and Ma (2011) argue that if BISP can actually improve women's decision-making power, it will definitely improve human development indicators such as health, education and nutrition as women tend to spend more on these items as compared to men. The mere fact that BISP redefined entitlements from the 'household' to the 'family' and identified the female as head of the unit is a major departure from earlier social protection programs in Pakistan (Holmes and Jones 2010). Using data between 2011 and 2013, Ambler and De Brauw (2017) statistically identify impacts which show that the BISP transfer has a substantial, positive impact on some variables measuring women's decision-making power and empowerment. On the other hand, Hou's (2016) empirical work found no clear evidence that higher women's decision-making power leads to better nutrition but did find a strong association between women's decision-making power and girls' education in rural localities. Khan and Qutub (2010) in their study report that the general impression of the survey team was that female recipients of the program did feel empowered by the cash transfer (women and men were interviewed separately). According to the authors, in a number of instances, men in beneficiary households responded that women were in fact in charge of income; female respondents were more likely to declare themselves heads of households when men were unemployed. Analysing phase II of the BISP program, the authors were critical of the poverty score card (PSC) indicators as no women-specific indicators were included in measuring the poverty status of a household as opposed to phase I of the program where, according to the authors, the politicians did value the gender dimension of poverty. Arshad (2011) reports that the BISP intervention improved women's sense of empowerment, enhanced their political participation and led to greater freedom in choices within households but the effect was larger among those women who were already earning incomes outside their homes. The author concludes that an income grant alone cannot enhance women's bargaining power unless the causal factors are addressed while formulating national policies and programs. Another study by Tahir et al. (2018) using both qualitative and quantitative methods in a district of Punjab reached a similar conclusion. They found that although BISP has enabled beneficiaries to commence or strengthen different enterprises under 'individually-led' or 'female-male partnership' models, it does not alter the patriarchal division of labour within families and does not help in economic or social empowerment of women. Using a difference-in-difference approach, Kashif (2016) found that women recipients in beneficiary households were making more sole and joint decision and were economically more active in comparison to women who do not receive BISP. The author, however, did not find a significant impact of the program on women's mobility. Overall, the author found only modest changes in women's access and control over resources, participation in decision-making and mobility of the beneficiary women. In the health arena, Hou and Ma (2012) found an insignificant association between women's decision-making power and institutional deliveries as other factors affect health services uptake by women. They point towards shortage of access to health facilities and the presence of influential male household members to be determining factors in improving women utilization of health facilities. In their synthesis paper, Holmes and Jones (2010) found that impact of social protection programmes on intra-household relations between women and men has become more complex. In some contexts, social protection has reduced tensions while in others it was either had a neutral effect or exacerbated the existing tensions. Overall, they find little evidence of any significant improvement in women's decision-making powers with the increased spending on social protection programmes.

A number of studies have examined the impact of BISP transfers on the lives of recipient households, especially on poverty reduction and its effects on improvement in health, education and other indicators of living standards. Nasir (2011) concluded that the BISP intervention played an effective role in mitigating the adverse impact of the global financial crisis at the household level. The study, which had a focus on the impact of the financial crisis on vulnerable households, found that the BISP was successful in increasing consumption at the household level especially for the vulnerable where the dependency ratio was higher in the case of women-headed households. The study was based on data obtained from the Pakistan Bureau of Statistics (PBS), namely the Household Integrated Economic Survey (HIES) and a Labour Force Survey (LFS). The paper also used data from a specifically designed Household Vulnerability Survey (HVS) of 1,000 vulnerable households. Based on a small data set in a sub-district of Punjab province, Naqvi et al. (2014) found that BISP transfers have brought structural stability in the lives of beneficiary households with provision of some relief to daily household expenditure on food, education and health. Ullah et al. (2015) found that BISP helped in women's empowerment as it promoted possession of CNIC among a large segment of the poorest women, as it was a necessary condition for program participation. According to his findings, possession of CNIC enabled beneficiary women to be included in the family tree of a household, which not only enabled them to access property rights but also enabled their participation in elections. Gazdar et al. (2013) found a similar impact as women got their identity cards made for the first time in their lives, which linked them to entitlements of citizenship. The author concluded that empowerment of women through engagement with BISP did occur in the process through owning a CNIC, provision of a reliable postal address, receiving postal orders and learning how to use an ATM. However, other more recent studies found that due to the small amount of the BISP transfer, most families spent the amount on immediate living consumption thus leaving little for spending on education and health (Mumtaz and Whiteford 2017, Waqas and Awan 2018). In a cross country review of social safety net programs (including BISP in Pakistan), Fiszbein et al. (2011) confirm that cash transfer programs were able to help weather the immediate effects of the 2008-09 economic crisis more effectively than past crises because of the greater prevalence of safety net programs.

A more recent study has focused on multiple aspects of BISP and provides a credible assessment of the effects of the program. Jalal (2017) evaluated the targeting performance of the BISP's PMT method and short-term welfare effects of BISP on household consumption, saving and debt, child welfare and female empowerment. The findings suggest that the BISP is subject to an under-coverage (exclusion) rate of 52.6% and an over-coverage rate (inclusion) of 73.6%. According to the author, PMT faced both design and implementation shortcomings which led to these large targeting errors. The PMT for BISP was developed based on 2005-06 data sets while the PMT survey was conducted in 2011 leading to errors by design. For instance, BISP chose to outsource the data collection process for PMT score to a variety of organizations (Partner Organizations or POs). This was a time when BISP's nascent organization was unable to supervise their work and according to Jalal (2017), this may have translated into inconsistency and measurement errors due to differences amongst the various organizations involved in the enumeration process. With regard to short-term welfare effects, Jalal (2017) found inconclusive effects on household savings, debts, food or child welfare. However, the study found significant improvements in most indicators of female empowerment. Haseeb and Vyborny (2016) quantify the impact of the Word Bank new policy design that was adopted to improve allocation of public spending under BISP by changing the targeting mechanism from politicians-based to PMT based targeting. The author found that the move reduced favouritism and substantially improved province-wide targeting which resulted in increased public legitimacy. However, the study focused only on the inclusion error while assuming low exclusion error in the PMT method. This assumption has no strong basis as the World Bank itself accepts high exclusion errors in the PMT design (World Bank 2009b).

A more rigorous assessment of the effectiveness and impact of the BISP program and its targeting process evaluation was sanctioned by BISP program office through external third party evaluators. Oxford Policy Management (OPM) carried out the impact evaluation studies while targeting process evaluation was done by GHK Consulting Limited. Sanctioned by the BISP, the purpose of these studies was to highlight the program's potential value and challenges as well as areas for additional policy interventions. These series of studies by OPM include a baseline survey report (Oxford Policy Management 2011) where it focused on 11 pre-agreed areas in which BISP is likely to have a potential impact. Based on a survey in 2011, this study found that 73% of the potentially eligible households were below the national poverty line. The study found that treatment households with Poverty Score Card (PSC) targeting of BISP were multidimensional poor as compared to the control households. The study used a Regression Discontinuity Design (RDD) to calculate the impact of the BISP intervention. Key findings of the assessment in 11 different areas found significant differences between those with and without the BISP intervention. The study however did not calculate inclusion and exclusion errors and only focussed on the phase when the PSC formula was being applied and did not examine targeting during the program's earlier phase, when politicians were entrusted with the task of identifying the poor. In a follow-up study (Oxford Policy Management 2014), based on data collected in 2014, OPM used both qualitative and quantitative methods to provide an analysis of BISP during the 3 years since the baseline round of 2011. The study found that over 3 years the program did help reduce poverty and its severity (Oxford Policy Management 2014). According to their results, the BISP led to a 19-percentage point reduction in poverty for the treatment group over 3 years. These findings, according to the study, are robust to different specifications. On the depth of poverty, the study found that the poverty gap fell by 3 percentage points for the treatment group as compared to the control group. According to the study, BISP also improved women's bargaining power in the household thus increasing women's role in household decision-making. The study also carried out a qualitative process evaluation and found weaknesses in the administration of Proxy Mean Testing (PMT) census, which may have cause mistargeting. However, the study's focus was mainly on impact evaluation of cash transfer on recipient lives and did not focus on the targeting performance of the program.

OPM's final impact evaluation study was conducted in 2016 using both quantitative and qualitative methods to evaluate the impact of BISP after 5 years of PMT method in place (Oxford Policy Management 2016). Using Regression Discontinuity Design, the study found evidence that BISP led to an increase in monthly food consumption of treatment households. BISP helped decrease deprivations in the living standards of the recipients, and improved how women are being viewed within the household and had statistically significant effects on the mobility of beneficiary women. The study further found that BISP helped in increasing the proportions of beneficiary women voting in elections probably because of women now holding a CNIC card because of BISP. BISP over the five year of grant disbursement did improve other livelihood indicators such as a reduction in reliance on casual labour, increase in ownership of livestock and increased savings. However, the final impact evaluation study did not find any significant increase in the proportion of beneficiary children attending school.

The most comprehensive evaluation of the targeting process of the PMT method of targeting for BISP was done by GHK Consultants (GHK Consulting Limited 2013). Their analysis covered four component of the Targeting Process Evaluation (TPE) including the targeting process, data entry, grievance complaints, and payments complaints. The evaluation particularly found serious drawbacks in the poverty scorecard census process including inefficiencies of partner organizations in implementing door-to-door survey, inadequate features of the scorecard and weak public information campaign. Most of the questionnaires for the Poverty Score Card (PSC) were filled in a central location as against the advice of door-to-door surveys thus seriously influencing the quality of the information collected. The evaluation found that these issues in the processes seriously reduced the quality of the targeting performance of the PMT method.

## 1.6 Current Research Questions & Data

The literature reviewed in the previous section shows that most of the available research on BISP focuses on evaluating the targeting performance of BISP grants under the PMT method, the role of the BISP in mitigating shocks to beneficiary households and its impact on health, education and consumption of the beneficiary households. Another large strand of the BISP literature concentrates on looking into its impact on women's empowerment, as women are the immediate beneficiaries of the grant. While all of these are important aspects of the BISP that need to be further studied, the current thesis departs from a focus on the effectiveness of one method of targeting or BISP effects on livelihood of beneficiary households. Explained in the following pages, current thesis focuses on less discussed but equally important aspects of BISP program with the objective to initiate a debate around the ignored aspect of cash transfer programs like BISP.

Instead of focusing on the PMT-based targeting method of BISP,[15]which has been examined by a number of authors, the thesis commences by first examining politicians-based targeting. The thesis uses countrywide PSLM data set for the year 2009-10 and examines targeting performance of BISP under Phase I of the program. Subsequently, chapter 3 examines the politics of distribution at a locality level when parliamentarians distributed BISP forms among different localities of a district. In particular, the chapter examines if equity and efficiency considerations influence the distribution of BISP forms or were political factors more important in shaping the distribution of BISP forms across different localities within a district. Building on the two previous chapters, particularly Chapter 2, Chapter 4 compares the targeting performance of community-based and proxy means targeting approaches. The chapter is based on a unique survey of some 3,151 households, which were reached both by politicians and the PSC survey.

In summary, the following three aspects will be looked into in three separate chapters:

a) Chapter 2 will rely on countrywide survey data to examine the performance of BISP targeting under Phase I, that is, when the program relied on community based targeting carried out by politicians.

b) Chapter 3 will focus on a single district and will examine whether there was political capture of BISP grants when it was targeted through politicians.

c) Chapter 4 will focus on a single district and will compare targeting performance of two methods, that is, community based targeting (CBT) carried out by politicians as compared to targeting based on a poverty scorecard (PSC) method.

To answer the above research questions, the current thesis makes use of both secondary and primary data. For the second chapter, the thesis uses the Pakistan Social and Living Standards Measurement (PSLM) survey data set for the year 2009-10. The data includes detailed modules on income, consumption, and other household socio-economic characteristics for the time when BISP targeting was through parliamentarians/politicians. The data is representative of all four provinces of Pakistan and its rural/urban bifurcation. The questionnaire developed for 2009-10 specifically included questions on BISP and other social protection programs. In this paper, inclusion and exclusion errors of the program will be calculated for Pakistan, rural-urban location and across different provinces to evaluate the targeting performance of the program.

For the third chapter, project data on all beneficiaries and non-beneficiaries is taken from the BISP project office. Data on 2008 election results of different national and provincial level constituencies is taken from the election commission of Pakistan. Locality-level election results of 2008 elections were compiled and arranged from the same data set. Census data from 1998 is used to estimate population and locality level socio-economic characteristics across 101 localities in the district. Special key informant discussions and focus group discussions were held in different localities of the district regarding important politicians and other powerful influential personalities in the 101 localities. The paper focuses on Swabi district in North-West province of Khyber Pakhtunkhwa of Pakistan.

For the fourth chapter, primary data from 24 randomly selected localities in district Swabi was collected through a detailed questionnaire specifically designed for this thesis. Enumerators and supervisors were trained in a 3-day training session to collect poverty profiles of more than 3,151 households using a questionnaire. Both enumerators and supervisors were also asked to rank each household in six different categories of poverty. Secondary data on the poverty scorecard of the BISP's PMT formulae was taken from the BISP program office and combined with the primary data.

## Notes

[1] https://sustainabledevelopment.un.org/sdg1

[2] The population figure of 186.2 million is an estimate as of 2016 and was reported in Pakistan's official economic survey. Provisional figures for the new Census 2017 are out and the total population as of 2017 stands at 207.7 million.

[3] The methodology used in the report to determine Pakistan's MPI is adopted from work on the global MPI, undertaken in collaboration with UNDP. Pakistan's MPI built upon the global MPI, retaining the same three core dimensions: education, health and living standards. In total 15 indicators are used in this national index where 3 indicators are on education, 4 indicators are on health and 8 indicators are on living standards. For details, please see (UNDP 2016b)

[4] http://www.finance.gov.pk/survey/chapters_17/15-Social_Safety_Nets.pdf

[5] See Appendix I for the 13 point criteria

[6] www.bisp.gov.pk

[7] Economic Survey of Pakistan, Finance Division, Government of Pakistan, 2015-16

[8] http://www.app.com.pk/cdwp-approves-pms-national-health-insurance-program/

[9] http://www.pmhealthprogram.gov.pk/faqs/

[10] http://www.dawn.com/news/1281267

[11] http://tribune.com.pk/story/1126698/bisp-launches-poverty-survey-says-official/

[12] http://bisp.gov.pk/nser/

[13] Economic Survey of Pakistan 2017-18 (Government of Pakistan 2018)

[14] Please see the section on the BISP website for details on the different payment mechanisms, http://bisp.gov.pk/cash-grant/#Mechanism946d-4435

[15] Increasingly, as may be expected, research focuses on the PMT-based targeting method of BISP as compared to politician-based targeting methods. BISP grants were targeted through politicians during the initial 3 years of the program, from FY 2009 till FY 2011, while the PMT method was adopted in end-2011 till now.

# 2 Targeting Performance of BISP under Parliamentarians Targeting

## 2.1 Targeted Interventions and Poverty Reduction

There is a consensus among researchers and policy makers that economic growth is a necessary but not sufficient condition for poverty alleviation (Godquin 2004, Dixon et al. 2007, Ravallion 2001) and that growth is not *all* that is needed to improve the lives of the poor (Dollar and Kraay 2002). While economic growth is necessary for sustainable poverty reduction, over the longer term, the very poor are unlikely to benefit from any "trickle-down" that may result from growth. In fact, to achieve sustainable economic growth, poverty has to be reduced so that the poorest of the poor can contribute to the growth of the economy. The challenge for policy is to combine growth-enhancing policies with the right anti-poverty policies to create opportunities for the poor, so that they too can contribute to growth (Ravallion 2004, Van de Walle 1998). The extent to which growth reduces poverty depends on the degree to which the poor participate in the growth process. Thus, in countries where growth is inadequate or is not pro-poor, there is a need to put in place mechanisms that reduce poverty and improve the ability of the poor to contribute to growth (DFID 2005, Ravallion 2004, Coady et al. 2004a). By providing regular and reliable support to poor households and helping the poor to invest in productive and capital-forming activities, targeted interventions can help in reducing high levels of persistent poverty and reverse the trend of increasing inequalities. Targeted interventions, such as safety nets, can also provide additional support in times of crisis to those who have temporarily fallen into poverty and assist them in a way that they are not forced to deplete their assets during times of hardship (Monchuk 2013). Governments in developing countries, aid donors and international agencies for development have recognized that poverty reduction cannot be achieved just by the promotion of economic growth. Targeted interventions are necessary to address the needs of the poorest and vulnerable groups to protect them from falling into poverty.

To directly reduce poverty, many countries in Asia, Africa and Latin America have adopted two different approaches to reach the poor. One is 'broad-targeting' in the form of spending on items that are needed by a large segment of society including the poor (for example, universal provision of primary education and health). The second approach is 'narrow-targeting' where the poor are identified and then benefits are conferred disproportionately to this group (Coady et al. 2004a).

During the 1960s and 1970s, the policies of broad targeting were preferred. However, since the 1980s, the balance has radically tilted in favour of narrow targeting in both developed as well as developing countries (Mkandawire 2005). Broadly targeted public expenditure reaches out to both the poor and non-poor equally but as poor have limited access to these services thus it benefits are marginal for the poor. Moreover, the quality of these public services tend to be very poor in most developing countries thus causing only little improvement in the lives of poor. Evidence from Pakistan shows that expenditure on infrastructure and health tends to benefit the non-poor disproportionately more than the poor (Gafar 2005). In contrast, narrow targeted transfers to poor households, if well targeted, reach the poor and vulnerable. This does not only increase the coverage of the poor but is also thought to be more cost effective compared to broad targeting measures (Van de Walle 1998).[1] Growing evidence from developing countries shows that direct 'social transfers' could help growth reach the very poor and vulnerable, and in countries where growth is slow, social transfers could reach the very poor directly, thus, reducing poverty (DFID 2005).

The terms 'social transfers', 'social protection', and 'social safety nets' are used interchangeably to refer to direct public interventions that are designed to protect vulnerable groups from shocks. Social transfers are defined as non-contributory transfer programs targeted to the poor or those vulnerable to poverty and shocks (Heltberg et al. 2007). These social transfers can take a variety of forms ranging from cash transfer (conditional or unconditional) to in-kind transfers of basic needs. Since the beginning of 1990s, there has been an emerging consensus that social safety nets designed to raise and protect the consumption level of poor households have a crucial role to play in poverty reduction and development (Mkandawire 2005). Similarly, transfers that are conditional on utilizing education and health services, contribute towards increasing human capital, which in turn helps reduce long-term poverty.

## 2.2 Pakistan's Experiences with Targeted Interventions

Pakistan's approaches to fighting poverty may be divided into two different periods, i.e., pre and post 2007. In 2006, a task force began working with the Planning Commission of Pakistan, which was formally mandated to draft a social protection strategy for the country. The Commission came up with an extensive National Social Protection Strategy (NSPS) in 2007 (Gazdar 2011). International organizations such as the World Bank (WB), the Asian Development Bank (ADB) and Department For International Development (DFID) assisted the Government of Pakistan and provided input to this strategy. The task force also reviewed existing programs at that time, which included programs on social assistance, social insurance, microfinance and public works programs. Before 2007, the programs targeted to reduce poverty were insufficient and did not have any significant impact on poverty reduction in Pakistan. These programs have serious gaps in design and implementation, and were fragmented; they also had low reach, and were under-funded (Gazdar 2011, Jamal 2010, Arif 2015, Jalan and Ravallion 1999, Balkenhol 2007, Coleman 2006, Arif 2006, Channa 2012).

With the return to democracy after the General Elections of 2008 in Pakistan, the new federal government incorporated NSPS 2007 into the Poverty Reduction Strategy Paper (PRSP-II). These two policy documents are crucial in delineating the social protection strategy of Pakistan before and after 2007, where NSPS represents the pre-2007 phase while the PRSP II represents the post-2007 phase.

The PRSP-II draws upon lessons learnt during the implementation of PRSP-I while taking into account the more recent political, economic and social events, which have had adverse impacts on Pakistan (Government of Pakistan 2007a). The PRSP-II is built upon nine pillars where the second pillar focuses on the protection of the poor and vulnerable. These government policy documents recognize that broadly targeted policies channel funds into sectors that are assumed to have a pro-poor impact like investments in infrastructure and the social sector. However, these documents also recognize the importance of targeted programs such as direct cash or in-kind transfer programs for the poor and vulnerable. The NSPS

& PRSP-II envisaged implementation of reforms over a five-year period, with a significant shift in focus towards cash transfer programs and public works (Gazdar 2011). Moreover, they highlight the design and implementation challenges noted in the relevant literature, and recommend the use of conditional cash transfers and proxy means testing methods for targeting as key improvements over previous anti-poverty interventions.

The constitution of Pakistan, in its second chapter on 'principles of policies' laid down the emphasis on 'promotion of social and economic well-being of the people'. Article 38 of the constitution categorically states that the State shall 'provide for all persons employed in the service of Pakistan or otherwise, social security by compulsory social insurance or other means; provide basic necessities of life, such as food, clothing, housing, education and medical relief, for all such citizens, irrespective of sex, caste, creed or race, as are permanently or temporarily unable to earn their livelihood on account of infirmity, sickness or unemployment; and reduce disparity in the income and earnings of individuals, including persons in the various classes of the service of Pakistan.[2]

After the election in February 2008, a coalition government was formed at the centre, headed by the Pakistan People's Party (a centre-left party). During the same time, due to a sharp increase in the prices of oil and other primary products, both internationally as well as domestically, Pakistan experienced double-digit inflation. This inflation almost halved the purchasing power of the poor and particularly affected them the most. The Government's response to the shocks was the introduction of the first-ever large cash transfer program through the setting up of the Benazir Income Support Program (BISP). To reiterate, due to the high inflation, there was an urgent need for direct and speedy relief to the underprivileged sections of society and the Benazir Income Support Program (BISP) was the Government of Pakistan's primary response to the situation.[3]

## 2.3 Targeting Mechanisms for Anti-poverty Programs and the BISP approach

Limited government budgets for poverty reduction, have led governments to devise narrow targeted programs, thus focusing program benefits on the poor and excluding the non-poor. The potential benefit of targeting is that it concentrates expenditures on those who need it most, which is expected to save money and improves program efficiency (Grosh 1994).

Targeting specific groups may be expected to achieve the maximum impact from a given budget or minimize budgetary costs to achieve a given impact (Kakwani et al. 2006). The success of any policy intervention, which directly targets benefits to the poor, should be judged by its ability to concentrate its benefits on the poor (Grosh 1994, Cornia and Stewart 1993). Transfer programs, that constitute safety nets, are more attractive because such transfers provide a benefit that is largely a private good for recipient households. In a review paper of targeting transfers in developing countries, Coady et al. (2004b) showed analytically that, through targeted transfers, one can eliminate inefficiencies arising from uniform transfers. Improved targeting screens non-poor household out of the program, thus both coverage of the poor and the benefit level going to the poor can be maximized. Coady et al. (2004a, 2004b) reviewed papers on 122-targeted anti-poverty interventions in 48 countries and showed that the median program transfers 25 percent more benefits to the poor than a universal or random allocation. However, they also found that as many as one-quarter of the programs reviewed have a regressive benefit incidence, meaning that the proportions of benefits going to the poor were less than the share of the poor in the population. A more recent review of the literature on anti-poverty programs, Devereux et al. (2017), finds results that are in line with previous review studies and concludes that targeting does increase the reach of program benefits to the poor but targeting is also associated with higher costs. Yusuf (2010) reviewed 30 community based targeted programs across the developing countries and found out that only 4 programs were regressive in their benefit distribution while all other programs were progressively delivering more benefits to the poor than to the non-poor. Poverty targeting of anti-poverty programs also depends a great deal on the nature and context of the project. Pradhan and Rawlings (2002) evaluated the Nicaragua Social Fund using propensity score matching and found mixed results for different social fund investments. The social fund interventions used geographical targeting or poverty mapping to direct resources to poor areas through poverty mapping and combined this with a demand driven approach (communities had to apply for funds). The authors found that most, but not all, social fund investments were well targeted towards poor communities and households. According to them, the self-targeted nature of some of the investments made them more pro-poor than other interventions.

 

While targeting of anti-poverty programs has obvious benefits, a number of methods exist for directing resources to a particular group. All targeting methods are designed to achieve the goal of identifying poor households, correctly and efficiently, for a given administrative capacity. The main targeting methods applied in practice are individual assessment, categorical targeting (tagging), self-targeting, and more recently community-based targeting (Coady et al. 2004a, Grosh 1994, Devereux et al. 2017, Morley and Coady 2003, White 2017, Yusuf 2010).

Individual assessment may be done through a verified mean test, proxy mean test or subjective evaluation by government agents or by members of the community. In Pakistan, as in other developing countries, the administrative capacity to deliver safety net interventions through verified means test is limited. That is because this method requires complete information on a household's income that verifies the collected information from independent sources. The administrative capacity to process and update this information entails a prohibitive cost.

Another method of individual assessment is through Proxy Means Testing (PMT), which utilizes observable characteristics of the households to generate a score for each household. These characteristics can be, for example; the location and quality of dwelling, ownership of durable goods, demographic structure of the household and the education level of household members, among other characteristics. In a PMT, the government collects information on assets and demographic characteristics to create a "proxy" for household consumption or income that is used for targeting (Alatas et al. 2012). However, this method also requires good administrative capacity and entails a high cost in carrying out screening of beneficiaries. Moreover, the unobservable characteristics of household poverty may render this method ineffective in incorporating the local definition of deprivation. Further, PMT incorporates only the permanent component of income by looking at the asset side of the household and thus may miss transitory shocks. Individual assessment may also be conducted by a government agent, who may be a member of the local bureaucracy, local community or NGO.

Other methods include categorical targeting and self-targeting. Categorical targeting or tagging offers eligibility to all members of a group identified by an easily identifiable characteristic or trait. These include geographical targeting of poor communities/localities, identification of vulnerable social groups such as single women with children, certain ethnic groups or the elderly (Conning and Kevane 2002, Robertson et al. 2014, Rai 2002). Self-targeting methods, on the other hand, have universal eligibility but the design involves dimensions that are thought to encourage the poorest to use the program and the non-poor not to do so. A stigma cost is associated with such programs for example a low wage public works scheme, price subsidies for inferior goods and the like.

Community based targeting of anti-poverty programs uses a group of community members to decide who in the community should benefit from the program. The principle function of these community members is not related to the program transfers. Conning and Kevane (2002) define community-based targeting as a state policy of contracting community groups or intermediary agents to have them carry out one or more of the following activities: (a) identify recipients for cash or in-kind benefits, (b) monitor the delivery of those benefits, and/or (c) engage in some of the delivery process. For example, a group of village elders may determine who receives grain provided for drought relief, or special committees composed of common community members or a mix of community members and local officials may be specially formed to determine eligibility for a program (Coady et al. 2004b).

The theoretical advantages and disadvantages of using community based targeting for anti-poverty programs are best summarized by Conning and Kevane (2002). They argue that besides lower cost of administration, community groups may screen the poor through better information for identification of their needs. Moreover, households may have less incentive to provide false information on assets, income or shocks. Community groups may also incorporate local definitions of deprivation and poverty thus overcoming the rigidity in national poverty line formulas. They, however, question the practicality of community-based targeting in some contexts. The capture of the program benefits by local elites, maintenance of minimal accounting records, and rent-seeking behaviour of the groups involved in the targeting may undermine the targeting efficiency of programs run by community groups. Besides elite and political capture of program benefits under community-based targeting, informational advantages within the community to deliver benefits to the poor may lead to a deterioration of existing societal tensions. Yusuf (2010) argues that community targeting is better attuned to communities where societal tensions and extreme disparity are not a pre-existing concern as otherwise powerful communities may exclude weaker and excluded segments of the community. For example, Yusuf (2010) found that community-based targeting programs in some developing countries exacerbated the exclusion of already excluded segments of population. In the context of South Asia, these community-based groups may serve to increase their local electoral base by screening out the opposition from the benefits of the program. However, it is generally believed, that local knowledge of families' living conditions may be more accurate than the results of a means test or a proxy means test. Seabright (1996) also makes the theoretical arguments that local information to reach the poor more effectively is one of the major advantages of targeting through local communities.

While characteristics of the two different targeting approaches of BISP program have been described in Chapter 1, a few details are worth repeating in the context of this section. Due to lack of data on who is poor and non-poor at the time of inception of the program, the BISP program used local political communities to assess an individual's eligibility for program benefits. These local political communities, who serve as agents for members of parliament, screened the eligibility of individuals under some broad criteria given by the program office. They carried out poverty assessment using their own judgement based on local information with some broad guidelines given by the BISP program office. In addition, the BISP program also used categorical targeting and tagged the elderly, widows, orphans and unemployed as eligible for the program. The stigma cost associated with the BISP program, in terms of the low benefits that it offers, was expected to keep the non-poor from applying to the program. Thus, at inception, the BISP targeting mechanism was a hybrid. However, the primary targeting mechanism was to rely on local political communities to identity the poor.

## 2.4 Empirical Evidence on Targeted Programs

Given the trade-offs between different methods of targeted anti-poverty programs, which method works best is ultimately an empirical question (Alatas et al. 2012). In a review of 122 targeted interventions in 48 countries, Coady et al. (2004b) examined the contested issue of efficiency of targeted interventions in developing countries. They found that a median targeted anti-poverty intervention transfers 25 percent more to poor individuals than do universal allocations, although a quarter of the programs were found to be regressive. Their result shows that with the rise in inequality, targeting performance of anti-poverty programs improves. They argued that in countries where inequality is more pronounced, targeting is pro-poor because differences in economic well-being are easier to identify. They also found that the use of more methods is associated with improved targeting, and each additional method improves performance by 15 percent. However, they found substantial variation within specific targeting methods, which suggests that differences in implementation are also important factors in determining the success of targeting the poor. Indeed, anti-poverty programs with similar targeting mechanisms may perform completely differently, depending on a country's institutions and context. Various review studies of targeted programs argue that there is no clearly preferred method for all programs or country contexts (Coady et al. 2004b, Devereux et al. 2017, White 2017). Coady et al. (2004a) showed that in a sample of programs, 80 percent of the variability was due to differences within targeting methods and only 20 percent due to differences across methods.

Prior to the launch of the BISP program in 2008, Pakistan experimented with different social safety net programs. These programs fall in the category of social assistance, social insurance, micro-finance and public works programs. The main programs under social assistance are Zakat, which is a cash transfer funded from a religious levy; Pakistan Bait-ul-Maal's Food Support Program (FSP) which is a tax funded cash transfer, Tawana (healthy) Pakistan which is a school-feeding program for girl students, and an untargeted wheat price subsidy. Under social insurance, the main programs are the Employees Old-age Benefit Institution (EOBI), the Workers' Welfare Fund (WWF), and the Employees' Social Security Institution (ESSI), all of which are funded using payroll levies on employers. In addition to these, the review of schemes in NSPS 2007 included microfinance and public works programs (Gazdar 2011). A variety of factors have contributed to the weak performance of safety net programs in Pakistan, including the prevalence of small, fragmented and duplicative programs; low spending levels resulting in insufficient coverage and low benefit adequacy; governance challenges resulting in infrequent and irregular payments to beneficiaries; and lack of transparent eligibility criteria (Heltberg et al. 2007). Arif (2006) evaluates the targeting efficiency of two programs in Pakistan, one a broadly targeted program (Lady Health Workers Program, LHWP) and the other a narrowly targeted program (The Zakat Program-a cash transfer to the poor). According to the study, LHWP could not reach the most disadvantaged areas due to supply side bottlenecks in program reach to rural areas. The cash transfer program of Zakat, where distribution of cash was assigned to the local community, was successful in reaching poor households particularly in rural areas but there were substantial leakages to relatively better-off households especially in the urban areas. These programs were thus, marred by low coverage, politicization and capture, and design problems (Arif 2006). Bari et al. (2005) reviewed seven selected social safety net programs[4] and found big gaps in existing social protection schemes especially in terms of their reach and targeting of the poorest of the poor. Jamal (2010) reviewed recent studies on social protection in Pakistan and found consensus among researchers that there was no clearly articulated government social protection framework before the introduction of BISP as all these programs were a series of ad-hoc responses to the problem of poverty and vulnerability. With the introduction of BISP, Pakistan now has a social protection program, which is further expanding its coverage and focus.

## 2.5 Measurement Strategy of Targeting Performance

The literature uses different measures to evaluate the targeting performance of anti-poverty programs. When program eligibility is based on imperfect information about who is poor, then the chances of exclusion (under coverage) and inclusion (leakages) errors are high. On the one hand, errors of inclusion occur when the program identifies the non-poor as poor and program benefits mistakenly flow to them (non-poor). On the other hand, errors of exclusion occur when the program identifies poor persons as non-poor, thus, denying them access to program benefits (Cornia and Stewart 1993). A frequently used method to evaluate the targeting performance of anti-poverty programs is to calculate these under-coverage and leakage rates. Under-coverage or type I error is the proportion of those poor households that are not included in program. Cornia and Stewart (1993) describe this as an F-mistake, that is, a failure in the prime objective of the intervention. Therefore, if the program did not correctly identify the poorest among the poor then it would be considered as under-coverage of those who need the program the most. On the other hand, when it comes to leakage, or the error of inclusion (Type II error or E-mistake), it is the proportion of those households who receive benefits while being non-poor. Both of these errors are undesirable and affect the performance of programs in reducing poverty. An elaborated version of the above is to find the benefit incidence of the program in different income groups.

This chapter estimates and examines these targeting errors for the BISP program. The chapter also uses an econometric approach to examine the targeting performance of the program intervention. The probability of receiving BISP is regressed against a set of proxy indicators of income and poverty status coupled with additional variables, which are included in the Pakistan Social & Living Standards Measurement (PSLM) survey.

## 2.6 Data Sources

This chapter is based on a household survey, Pakistan Social & Living Standards Measurement (PSLM) Survey 2009-10, carried out by the Pakistan Bureau of Statistics (PBS) with technical support from the World Bank. All urban and rural areas of four provinces were included in the survey with the exception of conflict zones and military restricted areas. A two-stage stratified sample design was adopted for the survey such that the data is representative at the province and urban/rural levels. Approximately, 6,980 households were sampled. The survey questionnaire included standard modules on demographic composition, employment, education, health, income, assets and expenditures. Specific modules were also included on shocks and the coping mechanisms adopted by households. Finally, on the request of the BISP program office, the survey also included special modules on social transfer programs including the BISP. The aim was to be able to identify the extent of coverage of these programs. As described in detail in section 1.3 of chapter 1, the survey was conducted at a time when BISP targeting was in Phase 1.

## 2.7 Descriptive Statistics and Bivariate Analysis

As a preview to a more rigorous benefit incidence and econometric analysis, this section provides a bivariate analysis of differences in a wide range of socio-economic attributes of BISP recipients and non-recipients.

Table 2.1 to 2.5 provides descriptive statistics for BISP recipients and non-recipients households, as well as for the full sample, for a set of selected variables to analyse differences between beneficiary and non-beneficiary households. The estimates in columns 1 to 3 in all tables are weighted means of the covariates of the full sample, BISP non-recipient sample and BISP recipient sample respectively while the last columns (column 4 in all tables) gives the differences of two means (of column 2 & 3) with the level of significance.

To start with, Table 2.1 gives descriptive statistics for differences in incomes and quintile distribution across the two set of samples. Descriptive statistics shows that, on average, BISP recipient households have significantly lower (40.7 %) average per capita annual incomes (Rs 20,398) as compared to (Rs 34,393) those households who are not receiving the BISP. The decomposition of the full sample into rural/urban areas indicates that average urban per capita incomes are much higher (Rs 42,317) than that of rural households (Rs 28,970), which shows the level of the rural-urban income divide in Pakistan. However, in the case of BISP recipient households, the difference between incomes of urban and rural households is insignificant. For the full sample, average per capita household incomes across provinces shows a lot of variation with the highest average per capita household incomes in Punjab at Rs 35,477 and lowest for Balochistan at Rs 23,117. With the exception of Balochistan, BISP recipient households have significantly lower per capita incomes in all three provinces as compared to the BISP non-recipient households. In the case of Balochistan, however, there is no significant income difference among the beneficiary and non-beneficiary households. Overall, across provinces, average incomes of beneficiary households are substantially lower in Punjab and Sindh as compared to beneficiary households in Khyber Pakhtunkhwa & Balochistan. In Baluchistan, which is the poorest among the four provinces, there is no difference in incomes between recipient and non-recipient households. This indicates, on priori grounds, relatively good targeting in Punjab and Sindh as compared to the other two provinces.

Decomposing the full sample into different consumption quintiles shows that BISP grants are mainly concentrated in the lowest three quintiles with maximum benefits going to the households in the poorest quintile. However, there are some leakages to the non-poor groups. Households belonging to the poorest quintile received the maximum share (36%) and the share declines as we move to the upper most quintiles (6%). Almost 84% of the BISP recipients belong to the three lowest consumption quintiles while the remaining 16 % of recipients are in the richer quintile groups. Around 60.2% of the people in Pakistan were living below the $2 a day poverty line in 2008[5], suggesting that the bulk of the benefits does flow to those who are below the poverty line.

***Table 2.1***
*Means of Covariates: Recipients vs Non-Recipients Differences in Incomes & Quintile Distribution*

| *Characteristics* | *(1) Full Sample* | *(2) Non-recipients* | *(3) BISP recipients* | *(2)-(3) Difference* |
|---|---|---|---|---|
| **Annualized Per Capita Income in Rs. (Region-wise)** | | | | |
| All Pakistan | 33,587 | 34,393 | 20,398 | 13,995*** |
| Urban | 42,317 | 43,259 | 20,926 | 22,333*** |
| Rural | 28,970 | 29,586 | 20,219 | 9,367*** |
| Punjab | 35,477 | 36,120 | 18,912 | 17,208*** |
| Sind | 31,699 | 32,859 | 16,744 | 16,115*** |
| Khyber Pakhtunkhwa | 31,191 | 31,867 | 26,398 | 5,469*** |
| Baluchistan | 23,117 | 23,181 | 22,331 | 850 |
| **Consumption Quintiles** | | | | |
| Quintile 1 | 0.20 | 0.19 | 0.36 | -0.17*** |
| Quintile 2 | 0.20 | 0.20 | 0.26 | -0.06** |
| Quintile 3 | 0.20 | 0.20 | 0.23 | -0.03 |
| Quintile 4 | 0.20 | 0.21 | 0.10 | 0.11*** |
| Quintile 5 | 0.20 | 0.20 | 0.06 | 0.15*** |

*Significance Levels* (*=10%,**=5%, ***=1%). No of observations: 6,980

Table 2.2 gives descriptive statistics of differences between BISP recipient and non-recipient households in their composition, educational and employment characteristics. Regarding household composition, BISP recipient households have more female-headed households, larger family sizes and are more likely to consist of widowed and divorced female members as compared to BISP non-recipient households. However, there are no significant differences between the two categories regarding share of dependent family members in the households. The only exception is the share of male members in the age group 18 to 65 years (which is supposed to be the main income earning group) where BISP recipient households have significantly fewer members as to those of non-BISP recipients. Overall, composition of BISP recipient households reflects a higher level of "at risk of poverty and hardships" as compared to non-recipient households.

With regard to household educational characteristics, non-recipient households have, on average, better indicators than those families who received BISP grants. The highest educational attainment level of any member in the household across the two groups shows that BISP non-recipient households are relatively well educated especially at the higher secondary and higher level of education as compared to BISP recipient households. The share of BISP recipient households with no education is significantly higher at 30% when compared to 21% amongst the non-recipient households. Similarly, on average more children go to school in non-recipients households as compared to recipient households, although the number of school going children is higher in the BISP sample, though not statistically significant. Another measure related to education is the affordability of a private school in the household. Here again, some 32 % of BISP non-recipient households send at least one child to high-cost private school as compared to only 15 % among the BISP recipient households.

Household employment characteristics shows that BISP recipient households are employed in low paid occupations such as daily wages as compared to non-recipient households. However, on other employment characteristics, such as presence of child labour in the household, household head as unemployed and women paid work in the household, there are no significant differences between the BISP recipient and non-recipient households.

***Table 2.2***
*Means of Covariates: Recipients vs Non-Recipients Differences at Households Level*

| *Characteristics* | *(1) Full Sample* | *(2) Non-recipients* | *(3) BISP recipients* | *(2)-(3) Difference* |
|---|---|---|---|---|
| **Household Composition** | | | | |
| Female headed HHs | 0.11 | 0.11 | 0.14 | -0.03 |
| HH size | 6.78 | 6.76 | 7.15 | -0.39* |
| HHs has a widow | 0.18 | 0.17 | 0.31 | -0.14*** |
| HHs has a divorcee | 0.02 | 0.01 | 0.04 | -0.02** |
| Share of male below age 18 | 22.5 | 22.5 | 21.6 | 0.94 |
| Share of male between age 18 & 65 | 24.2 | 24.3 | 22.5 | 1.79** |
| Share of male above age 65 | 2.41 | 2.36 | 3.32 | -0.96 |
| Share of female below age 18 | 21.9 | 21.9 | 21.8 | 0.14 |
| Share of female between age 18 & 65 | 26.6 | 26.6 | 27.5 | -0.97 |
| Share of female above age 65 | 2.26 | 2.21 | 3.15 | -0.94 |
| **Household Educational Characteristics** | | | | |
| No Education | 0.21 | 0.21 | 0.30 | -0.09*** |
| Primary | 0.18 | 0.18 | 0.20 | -0.02 |
| Middle | 0.14 | 0.14 | 0.17 | -0.03 |
| Secondary | 0.22 | 0.22 | 0.22 | 0.00 |
| Higher Secondary | 0.12 | 0.12 | 0.07 | 0.05*** |
| Higher | 0.13 | 0.14 | 0.05 | 0.09*** |
| Children attending school | 1.61 | 1.61 | 1.56 | 0.05 |
| Children of school age | 2.62 | 2.61 | 2.79 | -0.18 |
| Child in private school | 0.31 | 0.32 | 0.15 | 0.17*** |
| **Household Employment Characteristics** | | | | |
| child works | 0.06 | 0.06 | 0.05 | 0.01 |
| HH head unemployed | 0.20 | 0.20 | 0.23 | -0.03 |
| Ratio of Employed over Unemployed | 1.14 | 1.14 | 1.13 | 0.01 |
| Woman works | 0.14 | 0.14 | 0.16 | 0.02 |
| Occupation (Low paid) | 0.08 | 0.08 | 0.09 | 0.00 |
| Occupation | 0.52 | 0.52 | 0.66 | -0.15*** |
| Occupation | 0.30 | 0.31 | 0.21 | 0.09*** |
| Occupation (High paid) | 0.09 | 0.09 | 0.04 | 0.05*** |

*Significance Levels* (*=10%,**=5%, ***=1%). No of observations: 6,980

Table 2.3 provides descriptive statistics of differences in household living conditions between BISP recipient and non-recipient households. On availability of clean drinking water in the house, non-recipient households are significantly better off than BISP recipient households. For example, access to a motorized pump to extract clean ground water is 7 percentage points higher among non-BISP recipients. Similarly, access to utilities such as telephone and gas is substantially higher for non-recipient households (11 percentage points higher in case of telephone availability and 13 percentage points higher in case of gas availability) as compared to recipient households.

With regard to toilet and sewerage facilities in the house, there are again significant differences between recipient and non-recipient households. For example, houses having toilets, which are connected to the sewerage system is significantly higher amongst non-BISP households (22%) as compared to the BISP-recipient households (9%). Similarly, the use of unhygienic dry pit toilets is significantly higher among the BISP recipient households as compared to the non-recipient households. On connectivity with underground sewerage facility, BISP non-recipient households are significantly better off than the recipient households. According to our data, 22% of BISP non-recipient households are connected with underground sewerage as compare to only 9% of the BISP recipient households. Similarly, houses which are not connected with any kind of sewerage system are higher, by 12%, for the households who are receiving BISP benefits as compared to the non-recipient households. Overall, differences in the housing conditions of recipient and non-recipient households depict that the poverty condition of the recipient households are much worse than the BISP non-recipient households.

***Table 2.3***
*Means of Covariates: Recipients vs Non-Recipients Differences in Condition at House Level*

| *Characteristics* | *(1)* *Full Sample* | *(2)* *Non-recipients* | *(3)* *BISP recipients* | *(2)-(3)* *Difference* |
|---|---|---|---|---|
| **Sources of Drinking Water (1/0)** | | | | |
| Motorized pump | 0.29 | 0.29 | 0.23 | 0.07* |
| **Utilities in House (1/0)** | | | | |
| Telephone | 0.19 | 0.20 | 0.09 | 0.11*** |
| Gas | 0.38 | 0.39 | 0.26 | 0.13*** |
| Electricity | 0.93 | 0.93 | 0.95 | -0.02 |
| **Toilet Facility (1/0)** | | | | |
| Flush + Sewerage | 0.22 | 0.22 | 0.09 | 0.14*** |
| Flush + Pit | 0.33 | 0.33 | 0.39 | -0.07* |
| Flush + open drain | 0.18 | 0.18 | 0.13 | 0.05** |
| Dry Raised toilet | 0.06 | 0.05 | 0.12 | -0.07*** |
| Dry Pit toilet | 0.06 | 0.06 | 0.13 | -0.07*** |
| No toilet | 0.16 | 0.16 | 0.15 | 0.01 |
| **Sewerage Facility (1/0)** | | | | |
| Sewerage (underground) | 0.21 | 0.22 | 0.08 | 0.14*** |
| Sewerage (covered) | 0.02 | 0.02 | 0.03 | -0.01 |
| Sewerage (open drain) | 0.43 | 0.43 | 0.44 | -0.01 |
| No Sewerage | 0.34 | 0.33 | 0.45 | -0.12*** |

*Significance Levels* (*=10%,**=5%, ***=1%). No of observations: 6,980

Table 2.4 contains descriptive statistics of differences in movable and immovable assets for the BISP recipient and non-recipient households. BISP recipient households are less likely to possess various movable assets compared to the non-recipient households except for a few items, which are considered necessities in Pakistan. For example, 43% of the non-recipient households own a refrigerator as compared to only 22% in the case of BISP recipient households. Similarly, only 10% of the BISP recipient households own a motorbike as compared to 24% of the non-recipient households. In case of immovable assets, BISP non-recipient households are better off as compared to BISP recipient households. For example, 95% of BISP non-recipient households have some agricultural land as compared to only 39% of BISP recipient households. However, agriculture as a main source of income is not significantly different across the two groups.

**Table 2.4**
*Means of Covariates: Recipients vs Non-Recipients Differences in Household Assets*

| *Characteristics* | *(1) Full Sample* | *(2) Non-recipients* | *(3) BISP recipients* | *(2)-(3) Difference* |
|---|---|---|---|---|
| **Household Movable Assets (1/0)** | | | | |
| Refrigerator | 0.41 | 0.43 | 0.22 | 0.20*** |
| Freezer | 0.04 | 0.04 | 0.03 | 0.01 |
| Air-condition | 0.05 | 0.05 | 0.00 | 0.05*** |
| Air cooler | 0.07 | 0.07 | 0.03 | 0.04*** |
| Fan | 0.89 | 0.89 | 0.89 | 0.00 |
| Greaser | 0.06 | 0.07 | 0.00 | 0.06*** |
| Washing Machine | 0.46 | 0.47 | 0.33 | 0.14*** |
| Camera | 0.02 | 0.02 | 0.00 | 0.02*** |
| Cooking stove | 0.42 | 0.43 | 0.26 | 0.17*** |
| Cooking range | 0.03 | 0.03 | 0.01 | 0.01** |
| Heater | 0.09 | 0.09 | 0.04 | 0.05*** |
| Bicycle | 0.30 | 0.31 | 0.25 | 0.06** |
| Car | 0.04 | 0.04 | 0.01 | 0.04*** |
| Motorcycle | 0.23 | 0.24 | 0.10 | 0.14*** |
| TV | 0.57 | 0.58 | 0.47 | 0.12*** |
| VCR | 0.01 | 0.01 | 0.01 | 0.00 |
| Radio | 0.14 | 0.14 | 0.17 | -0.03 |
| Cd player | 0.04 | 0.04 | 0.02 | 0.02* |
| Sewing machine | 0.53 | 0.54 | 0.46 | 0.08*** |
| Personal Computer | 0.13 | 0.13 | 0.07 | 0.06*** |
| **Immovable Assets (1/0)** | | | | |
| Agriculture land | 0.92 | 0.95 | 0.39 | 0.56** |
| Non-agricultural land | 0.02 | 0.03 | 0.01 | 0.01** |
| Residential building | 0.89 | 0.89 | 0.91 | -0.01 |
| Commercial Building | 0.03 | 0.04 | 0.01 | 0.02*** |
| Agriculture as source of income | 0.23 | 0.23 | 0.18 | 0.05 |

*Significance Levels* (*=10%,**=5%, ***=1%). No of observations: 6,980

Finally, Table 2.5 gives descriptive statistics of differences in household savings across BISP recipient and non-recipient households. Non-recipient households have significantly higher levels of savings in terms of cash and jewellery as compared to BISP recipient households. The BISP non-recipient households have average cash savings of Rs. 23,751, which is three times larger than the average savings of Rs. 7,511 of BISP recipient households. Similarly, BISP non-recipient households have twice (Rs. 54,082) the size of jewellery in savings, on average, as compared to BISP recipient households (Rs. 29,132). On the other hand, BISP recipients are more burdened with loans as compared to non-recipients, though the difference is statistically insignificant.

The second part of Table 2.5 examines whether households in the two groups participate in other anti-poverty programs or not. It shows that BISP recipient households' participation in other anti-poverty programs is significantly higher than non-recipient households. Combining participation in all anti-poverty programs (including participation in private zakat which is a religious charity by the rich directed towards the poor as a religious obligation), there is a larger proportion (30.5%) of BISP recipient households who participate in other anti-poverty programs as compared to non-recipient households (4.1%). This shows that BISP recipient households are also those households who are chosen by the rich for their religious charity as 27 % of the BISP recipient households received private zakat as against 2.4% of the BISP non-recipient households.

***Table 2.5***
*Means of Covariates: Recipients vs Non-Recipients Differences in Household Savings & Participation in other Anti-Poverty Programs*

| Characteristics | (1) Full Sample | (2) Non-recipients | (3) BISP recipients | (2)-(3) Difference |
|---|---|---|---|---|
| **Savings & Loans** | | | | |
| Savings (in Rs.) | 22,816 | 23,751 | 7,511 | 16,241*** |
| Jewellery (in Rs.) | 52,645 | 54,082 | 29,132 | 24,950*** |
| Loans (in Rs.) | 23,344 | 23,233 | 25,168 | -1,935 |
| **Participation in Other Welfare Programs** | | | | |
| Government Zakat | 0.004 | 0.003 | 0.015 | -0.012** |
| Pakistan Bait ul Maal | 0.005 | 0.003 | 0.025 | -0.022** |
| Child support program | 0.003 | 0.002 | 0.011 | -0.009 |
| Rural Support program | 0.002 | 0.001 | 0.007 | -0.006 |
| Punjab food support program | 0.008 | 0.009 | 0.003 | 0.010** |
| Livelihood support program | 0.001 | 0.001 | 0.000 | 0.001 |
| Micro finance program | 0.001 | 0.001 | 0.001 | 0.000 |
| Any other support program | 0.009 | 0.009 | 0.023 | -0.014* |
| All Programs | 0.031 | 0.028 | 0.081 | -0.053*** |
| Private Zakat | 0.038 | 0.024 | 0.270 | -0.246*** |
| All Programs +Private Zakat | 0.056 | 0.041 | 0.305 | -0.264*** |

*Significance Levels* (*=10%,**=5%, ***=1%). No of observations: 6,980

## 2.8 The Results

### 2.8.1 Overall Benefit Incidence

Table 2.6 examines the distribution of BISP benefits across Pakistan. The distribution of BISP benefits by groups of quintiles of annualized per capita income (Table 2.6) shows that 10.38% of those in the lowest income quintile received the BISP (column 7) while the corresponding figures are 7.34% and 6.51% in quintiles 2 and 3. The percentage of program recipients is lower for the richer quintiles with 2.77% and 1.70% for quintiles 4 and 5, respectively. The overall reach of the BISP program is about 5.76% of the total population. Column 8 shows the odds ratio of receiving BISP benefits which is the incidence of benefits for a particular sub-group of the population divided by the average incidence. This ratio reflects the odds of selection of a household in a particular group to receive the benefits as compared to the whole population. An odds ratio greater than 1 for a particular sub-group implies greater likelihood of receiving benefits. According to the results, the three poorest quintiles have odds ratios greater than 1 as compared to the two richer quintiles showing the odds of selection of a household become lower as a household becomes richer.

The sixth column in table 2.6 shows the percentage share of BISP recipients for different income quintile groups of the population. The results show that the share of households who are in the lowest quintiles is highest while it falls as we move from the poorest income quintiles to richer quintiles depicting a pro-poor tendency of the program. The first, second and third income quintiles receive a share of 36%, 25% and 23% respectively which means 84% of the BISP households are from the lowest 3 quintiles. Given that in 2008, 60.2% of the population in Pakistan was living under $2 a day, the program seems to be relatively pro-poor, although 16% of the recipients maybe considered non-poor. Ideally, the benefits should be flowing only to the poorest of the poor, however, it seems that the political workers who distributed the BISP forms among the recipients were unable to differentiate within the category of poor households.

***Table 2.6***

*Distribution of BISP Benefits (Average Benefit Incidence) All Pakistan*

| | *Full Sample* | | | *BISP Sample* | | | *Benefit Incidence* | |
|---|---|---|---|---|---|---|---|---|
| ***Income Quintiles*** | ***Annual-ized PC Income (1)*** | ***Number of HHs (2)*** | ***Shar e (%) (3)*** | ***Annual-ized PC Income (4)*** | ***Number of HHs (5)*** | ***Sha re (%) (6)*** | ***Average incidence (in %) (7)*** | ***Odds ratio (8)*** |
| **ALL Pakistan** | | | | | | | | |
| Quintile 1 | 11,553 | 1376 | 20 | 11,401 | 160 | 36 | 10.38 | 1.81 |
| Quintile 2 | 17,470 | 1475 | 20 | 17,407 | 143 | 25 | 7.34 | 1.28 |
| Quintile 3 | 23,992 | 1519 | 20 | 23,627 | 124 | 23 | 6.51 | 1.13 |
| Quintile 4 | 33,969 | 1330 | 20 | 33,555 | 64 | 10 | 2.77 | 0.48 |
| Quintile 5 | 82,166 | 1280 | 20 | 55,056 | 32 | 6 | 1.70 | 0.30 |
| All | 33,587 | 6980 | 100 | 20,398 | 523 | 100 | 5.76 | 1.00 |

*Source*: Author Calculations from Pakistan Social & Living Standard Measurement Survey 2009-10.

## 2.8.2 Geographical Divide and Targeting of the Program

### *I. Rural/Urban Divide*

Table 2.7 provides data on benefit incidence in rural and urban parts of the country. There are significant differences regarding the concentration and coverage of BISP in rural/urban locations. About 70% of the rural population lies in the bottom three quintiles while the corresponding figure for urban areas is 43%. In terms of access to the BISP, both in rural and urban localities, around 85% of the beneficiaries lie in the first three quintiles. However, in rural areas the share of the poorest quintile is higher (40%) as compared to their share in urban areas (23%). It seems that it was easier for political workers to distinguish among different groups of poor in rural areas as compared to urban areas, probably due to closer networks in rural areas as compared to urban areas. Similarly, the overall average incidence of the BISP grants is higher (6.6%) in rural areas as compared to urban areas (4.2%). Thus, while there are significant differences in quintile-wise distribution across rural and urban locations the bulk of the beneficiaries (85%) are poor in both rural and urban areas.

***Table 2.7***
*Distribution of BISP Benefits (Average Benefit Incidence) Rural/Urban*

| *Income Quintiles* | *Full Sample* | | | *BISP Sample* | | | *Benefit Incidence* | |
|---|---|---|---|---|---|---|---|---|
| | *Annualized PC Income (1)* | *Number of HHs (2)* | *Share (%) (3)* | *Annualized PC Income (4)* | *Number of HHs (5)* | *Share (%) (6)* | *Average incidence (in %) (7)* | *Odds ratio (8)* |
| **RURAL** | | | | | | | | |
| Quintile 1 | 11,450 | 1112 | 26 | 11,313 | 128 | 40 | 10.19 | 1.69 |
| Quintile 2 | 17,427 | 1032 | 23 | 17,311 | 94 | 23 | 6.69 | 1.11 |
| Quintile 3 | 23,892 | 974 | 21 | 23,744 | 88 | 21 | 6.53 | 1.08 |
| Quintile 4 | 33,603 | 671 | 15 | 33,939 | 36 | 8 | 3.57 | 0.59 |
| Quintile 5 | 81,056 | 551 | 15 | 54,388 | 26 | 7 | 3.15 | 0.52 |
| All | 28,970 | 4340 | 100 | 20,219 | 372 | 100 | 6.58 | 1 |
| **URBAN** | | | | | | | | |
| Quintile 1 | 12,147 | 264 | 9 | 11,853 | 32 | 23 | 11.48 | 1.95 |
| Quintile 2 | 17,593 | 443 | 15 | 17,607 | 49 | 33 | 9.2 | 1.56 |
| Quintile 3 | 24,209 | 545 | 19 | 23,375 | 36 | 29 | 6.46 | 1.1 |
| Quintile 4 | 34,343 | 659 | 29 | 32,837 | 28 | 13 | 1.95 | 0.33 |
| Quintile 5 | 83,209 | 729 | 29 | 61,136 | 6 | 2 | 0.33 | 0.06 |
| All | 42,317 | 2640 | 100 | 20,926 | 151 | 100 | 4.22 | 1 |

*Source*: Author Calculations from Pakistan Social & Living Standard Measurement Survey 2009-10.

### *II. Provincial Divide*

There are marked differences in the distribution of program beneficiaries across provinces, as shown in Table 2.8. The proportion of households that received the BISP grant was highest in Khyber Pakhtunkhwa (12.4%), followed by Baluchistan (7.6%) and Sindh (7.2%) while program incidence in Punjab was the lowest (3.7%). As per the most recent poverty figures (UNDP 2016b), poverty incidence in Punjab is the lowest at 31.4%, followed by Sindh (43.1%), Khyber Pakhtunkhwa (49.2%) and Balochistan (71.2%). In principle, since the same number of BISP forms was distributed to each parliamentarian, regardless of the province, and the share of parliamentarians is based on a province's population, the proportion of beneficiaries in each province should be the same. However, this is not the case.[6]

Regardless of the overall distribution of forms, Table 2.8 provides estimates of the within-province allocation of the BISP. The share of BISP benefits going to the lowest quintile is highest in Sindh (52%) followed by Punjab (38%) while Khyber Pakhtunkhwa and Balochistan perform poorly with a benefit incidence rate of 20% and 12%, respectively, in terms of targeting the poorest among the poor. However, in the case of Balochistan, some 42% of the share of the grants went to the second poorest quintile. The share of BISP grants going to the lowest three quintiles (calculated on the full sample basis) is 95% in Sindh and 86% in Punjab. In Khyber Pakhtunkhwa and Balochistan, the corresponding figures are 72% and 80%, respectively. In summary, the distribution of BISP forms in Sindh is better than the national average; it is about the national average in Punjab and is below national average in the provinces of Khyber Pakhtunkhwa and Balochistan.

Average benefit incidence (column 7) displays substantial variation across provinces. In Punjab, 7.49% of those in the poorest quintile received the BISP grants as compared to only 0.6% of those in the richest quintile. In Sindh, 15.6% of those in the poorest received the BISP as compared to only 0.6% of those in the richest. In Khyber Pakhtunkhwa (KP) and Balochistan provinces, the distribution of grants is more evenly spread out. In KP, 10.5% of those in the richest quintiles received benefits and in Baluchistan it was 4%. Thus, while leakages are limited in the case of Punjab and Sindh, they are substantial for the other two provinces.

With the exception of Balochistan, the odds ratios for the first three quintiles in all provinces is higher than 1 showing a greater chance of getting BISP benefits for the poorest three groups (column 8).

**Table 2.8**

*Distribution of BISP Benefits (Average Benefit Incidence) Provinces*

| Income Quintiles | Full Sample | | | BISP Sample | | | Benefit Incidence | |
|---|---|---|---|---|---|---|---|---|
| | Annualized PC Income (1) | Number of HHs (2) | Proportion (3) | Annualized PC Income (4) | Number of HHs (5) | Proportion (6) | Average incidence (in %) (7) | Odds ratio (8) |
| **Punjab** | | | | | | | | |
| Quintile 1 | 11,424 | 530 | 0.19 | 11,216 | 43 | 0.38 | 7.49 | 1.93 |
| Quintile 2 | 17,476 | 541 | 0.18 | 17,215 | 29 | 0.27 | 5.4 | 1.4 |
| Quintile 3 | 24,149 | 580 | 0.2 | 23,411 | 25 | 0.22 | 4.06 | 1.05 |
| Quintile 4 | 33,956 | 582 | 0.2 | 33,066 | 13 | 0.1 | 1.79 | 0.46 |
| Quintile 5 | 83,073 | 697 | 0.22 | 47,172 | 4 | 0.04 | 0.61 | 0.16 |
| All | 35,477 | 2930 | 1 | 18,912 | 114 | 1 | 3.74 | 1 |
| **Sindh** | | | | | | | | |
| Quintile 1 | 11,546 | 455 | 0.24 | 11,509 | 72 | 0.52 | 15.57 | 2.34 |
| Quintile 2 | 17,424 | 381 | 0.22 | 17,603 | 29 | 0.22 | 7.27 | 1.09 |
| Quintile 3 | 23,860 | 326 | 0.18 | 23,658 | 26 | 0.21 | 8.29 | 1.25 |
| Quintile 4 | 34,254 | 271 | 0.2 | 31,644 | 6 | 0.04 | 1.56 | 0.23 |
| Quintile 5 | 84,572 | 236 | 0.17 | 49,288 | 2 | 0.01 | 0.58 | 0.09 |
| All | 31,699 | 1669 | 1 | 16,744 | 135 | 1 | 7.2 | 1 |
| **KPK** | | | | | | | | |
| Quintile 1 | 12,065 | 210 | 0.17 | 11,464 | 33 | 0.2 | 15.03 | 1.21 |
| Quintile 2 | 17,558 | 283 | 0.21 | 17,466 | 41 | 0.25 | 14.47 | 1.17 |
| Quintile 3 | 23,656 | 322 | 0.24 | 24,001 | 42 | 0.26 | 13.79 | 1.11 |
| Quintile 4 | 33,587 | 299 | 0.22 | 34,798 | 26 | 0.14 | 8.13 | 0.66 |
| Quintile 5 | 74,224 | 262 | 0.17 | 58,675 | 21 | 0.14 | 10.48 | 0.85 |
| All | 31,191 | 1376 | 1 | 26,398 | 163 | 1 | 12.35 | 1 |
| **Baluchistan** | | | | | | | | |
| Quintile 1 | 12,095 | 181 | 0.23 | 12,711 | 12 | 0.12 | 3.8 | 0.54 |
| Quintile 2 | 17,423 | 270 | 0.3 | 17,576 | 44 | 0.42 | 10.41 | 1.48 |
| Quintile 3 | 23,622 | 291 | 0.27 | 22,946 | 31 | 0.27 | 7.66 | 1.08 |
| Quintile 4 | 33,660 | 178 | 0.13 | 33,090 | 19 | 0.16 | 9.35 | 1.32 |
| Quintile 5 | 62,634 | 85 | 0.07 | 53,726 | 5 | 0.04 | 4.07 | 0.58 |
| All | 23,117 | 1005 | 1 | 22,331 | 111 | 1 | 7.57 | 1 |

*Source*: Author Calculations from Pakistan Social & Living Standard Measurement Survey 2009-10.

### 2.8.3 The BISP's targeting: Probit Estimates

As discussed earlier, BISP program grants were allocated by political agents on basis of their knowledge of local circumstances. This section estimates various probit specifications of the probability of receiving a BISP grant as a function of a range of observable characteristics of a household. The idea is to examine whether there is a systematic relationship between allocation of BISP benefits and observable traits that are often used to proxy poverty. Table 2.9 provide marginal effects of the probit estimate. The standard errors are adjusted for the stratified sampling design of the survey.

Table 2.9 provides estimates based on eight different specifications. The first specification (column 1) includes only the distribution of population into different income quintiles; column 2 adds provinces, province interactions with income quintiles and the rural location to capture geographical targeting. The models in columns 3 to 8, sequentially include additional explanatory variables and are reported in appendix III.

All eight specifications show that there are significant negative effects of per capita income on the probability of receiving a BISP grant. The effect declines when more explanatory variables are added to the model but the effect is still significant in all specifications. Households in the richest quintile are 6 percentage points (specification 1) less likely to get a BISP grant relative to households in the poorest quintile. This effect falls to 3.2 percentage points in specification 8$^{th}$ given in column 8. All these marginal effects are statistically significant. This corresponds to our earlier findings through simple benefit incidence analysis where our results showed that the richer the household, the lower the probability of receiving BISP benefits.

In the second model (column 2), we include provinces and their interaction terms with different quintiles to examine geographical variation in program distribution. Compared to the control group of living in Punjab and belonging to the poorest quintile, a household living in Sindh and KP is 4.6 and 4.7 percentage point more likely to get BISP benefits, respectively. However, there are no significant differences for the same quintile group living in Punjab and Balochistan. Including the interaction term of province with different quintiles, the richest quintile group in Sindh has a 1.8 percentage more probability to receive BISP grants as compared to the same group from Punjab. In Khyber Pakhtunkhwa & Balochistan, the leakages are more pronounced (19.1% and 20.1% respectively) if we compare it to the same group in the province of Punjab.

Other models (column 3-8) further include variables that constitute the selection criteria of the poverty scorecard which was adopted in the second phase of the program for targeting poor households. These are a wide range of variables including the size of the household, its composition and employment levels, gender and education of the head of the household, number of children and school-going children, number of rooms in the house, type of toilet used in the house, ownership of various household durables, livestock & agricultural land. The specifications also include other characteristics such as sewerage facilities at the house, presence of household utilities, movable and non-movable assets, sources of drinking water and whether or not the household lives in a rural area.

Based on the full-set of estimates, that is, column 8 we see that the receipt of BISP grants is negatively related to the level of per capita income. The marginal effects range from 1.1 to 3.2 percentage points, depending on the quintile. With regard to the quintile and provincial interaction terms, very few of the interactions are now statistically significant, although, it is still the case that the richest quintiles in KP are more likely to obtain benefits. Despite greater prevalence of poverty in rural areas, after controlling for an array of variables, living in a rural area is significantly associated with a slightly lower probability of obtaining a BISP grant as compared to living in urban area. It is possible that despite the high concentration of poverty in Pakistan's rural areas (Government of Pakistan 2016, UNDP 2016a, UNDP 2016b), politicians were unable to reach out to poor households in rural areas. As discussed earlier in the current chapter, informational disadvantages, inaccessibility, and lower density of population in rural areas are the possible reasons for the lower probability of receiving a BISP grant from a politician as compared to living in an urban area.

Regarding household composition and other household characteristics, the size of the family and whether a family is headed by a female, has no significant effects on the probability of receiving BISP forms. However, if a household has a widow, it significantly increases the probability of getting a BISP grant by 3 percentage points. This shows that politicians view widowed women as the only needy category while other household characteristics have little bearing on their choice of forms distribution. Politician's preference for widowed women is also guided by the instructions on BISP forms as well as socio-culture perceptions where, by default, a widowed woman is considered extremely poor.

With regard to educational characteristics, probability of selection into the program decreases by 1.4 percentage point (specification 8) if a household has at least one member who has attained a higher educational degree of an undergraduate or above. Similarly, if there is at least one child of the family going to a costly private school, then the probability of selection into the program decreases by 0.8 percentage point.

Employment characteristics have no significant effects on family selection into BISP, except if a child works in a family. The effect is negative and chances of selection into the program reduces by 1.1 percentage point if a child works. This suggests that political workers may have missed extremely poor marginalized families, where children engage in active work. As discussed in the section on benefit incidence analysis, all three of the lowest income quintile groups received substantial shares of the BISP benefits thus limiting the coverage of families in the first quintile where extremely marginalized households lie. Similarly, families living in more far-flung areas where they use ponds or other sources for drinking water are less likely to receive benefits.

There is no evidence of a relationship between the receipt of BISP benefits and the type of toilet and sewerage facilities in the household. On the presence of durables item in the household, probit estimates shows that there is a strong negative relationship between ownership of a range of households durable and receipt of BISP grants. Having a refrigerator, air-conditioner, geyser, cooking stove, car or computer in household significantly reduces the probability of selection into the program. The presence of a radio and TV set in a household is, however, positively related to the receipt of BISP forms. While a radio and a TV are household durables and are related to wealth, they are also sources of information and it appears that in this case their information role may be translating into a higher probability of getting access to BISP benefits.

On other assets and savings, only having a non-agricultural land is negatively related with the receipt of BISP grant while other variables have no relationship. Agriculture as a main source of income is also negatively related with the grant receipts.

**Table 2.9**
*Marginal Effects (Dependent Variable=whether household received BISP?)*

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| **Per Capita Income Quintile (i. Quintile 1, poorest=reference)** | | | | | | | | |
| ii. Quintile 2 | -0.018*** | -0.014 | -0.014* | -0.013* | -0.013* | -0.014** | -0.012** | -0.011** |
| | (2.75) | (1.59) | (1.75) | (1.66) | (1.69) | (2.20) | (2.34) | (2.30) |
| iii. Quintile 3 | -0.023*** | -0.023** | -0.024*** | -0.022** | -0.021** | -0.023*** | -0.019*** | -0.018*** |
| | (3.23) | (2.39) | (2.77) | (2.38) | (2.37) | (3.28) | (3.36) | (3.33) |
| iv. Quintile 4 | -0.050*** | -0.043*** | -0.041*** | -0.037*** | -0.035*** | -0.035*** | -0.027*** | -0.026*** |
| | (7.70) | (5.36) | (5.64) | (5.05) | (4.83) | (5.56) | (5.09) | (4.93) |
| v. Quintile 5 | -0.060*** | -0.059*** | -0.057*** | -0.050*** | -0.048*** | -0.046*** | -0.034*** | -0.032*** |
| | (9.13) | (7.45) | (7.88) | (6.99) | (6.49) | (7.11) | (6.05) | (5.87) |
| **Province (i. Punjab=reference)** | | | | | | | | |
| ii. Sindh | | 0.046** | 0.048** | 0.047** | 0.046** | 0.036** | 0.032** | 0.034** |
| | | (2.32) | (2.51) | (2.52) | (2.58) | (2.37) | (2.38) | (2.50) |
| iii. KPK | | 0.047* | 0.056** | 0.050** | 0.049** | 0.018 | 0.029 | 0.03 |
| | | (1.90) | (2.19) | (2.14) | (2.08) | (1.05) | (1.55) | (1.61) |
| iv. Baloch | | -0.023 | -0.013 | -0.013 | -0.014 | -0.017 | -0.014* | -0.013* |
| | | (1.64) | (0.82) | (0.87) | (1.01) | (1.63) | (1.89) | (1.73) |
| **Quintile * Province (Interaction Term) (i. Quintile 1 * Punjab=reference)** | | | | | | | | |
| ii. Quintile 2 * Sindh | | -0.020** | -0.019** | -0.017** | -0.017** | -0.013 | -0.011* | -0.010* |
| | | (1.99) | (2.24) | (2.05) | (2.08) | (1.59) | (1.78) | (1.79) |
| iii. Quintile 2 * KPK | | 0.014 | 0.008 | 0.009 | 0.008 | 0.012 | 0.011 | 0.012 |
| | | (0.67) | (0.46) | (0.51) | (0.44) | (0.66) | (0.76) | (0.80) |
| iv. Quintile 2 * Baloch | | 0.104* | 0.098* | 0.096* | 0.100* | 0.088* | 0.068 | 0.07 |
| | | (1.82) | (1.76) | (1.71) | (1.77) | (1.67) | (1.57) | (1.59) |
| v. Quintile 3 * Sindh | | -0.006 | -0.01 | -0.009 | -0.008 | -0.002 | -0.004 | -0.004 |
| | | (0.37) | (0.81) | (0.72) | (0.68) | (0.20) | (0.43) | (0.43) |
| vi. Quintile 3 * KPK | | 0.027 | 0.026 | 0.027 | 0.026 | 0.034 | 0.029 | 0.031 |
| | | (0.93) | (0.95) | (1.02) | (0.98) | (1.24) | (1.26) | (1.31) |
| vii. Quintile 3 * Baloch | | 0.096* | 0.095* | 0.092* | 0.099* | 0.083* | 0.058 | 0.062* |
| | | (1.85) | (1.84) | (1.79) | (1.87) | (1.79) | (1.62) | (1.68) |
| viii. Quintile 4 * Sindh | | -0.030*** | -0.029*** | -0.027*** | -0.026*** | -0.018** | -0.015** | -0.014** |
| | | (2.94) | (3.67) | (3.58) | (3.60) | (1.98) | (2.23) | (2.20) |
| ix. Quintile 4 * KPK | | 0.034 | 0.024 | 0.028 | 0.026 | 0.037 | 0.028 | 0.026 |
| | | (0.99) | (0.83) | (0.93) | (0.91) | (1.16) | (1.03) | (1.02) |
| x. Quintile 4 * Baloch | | 0.224** | 0.196* | 0.194* | 0.204* | 0.177* | 0.123 | 0.132 |
| | | (2.08) | (1.92) | (1.88) | (1.94) | (1.72) | (1.53) | (1.55) |
| xi. Quintile 5 * Sindh | | -0.028* | -0.028** | -0.024* | -0.023* | -0.015 | -0.014 | -0.014 |
| | | (1.79) | (2.22) | (1.85) | (1.76) | (1.00) | (1.44) | (1.56) |
| xii. Quintile 5 * KPK | | 0.144* | 0.133* | 0.138* | 0.135* | 0.151* | 0.125* | 0.119* |
| | | (1.84) | (1.73) | (1.80) | (1.80) | (1.93) | (1.81) | (1.79) |
| xiii. Quintile 5 * Baloch | | 0.217* | 0.202 | 0.219* | 0.229* | 0.229* | 0.151 | 0.169 |
| | | (1.72) | (1.61) | (1.68) | (1.73) | (1.70) | (1.47) | (1.55) |
| Rural | | -0.002 | -0.002 | -0.005 | -0.001 | -0.012* | -0.011* | -0.010* |
| | | (0.26) | (0.22) | (0.67) | (0.11) | (1.73) | (1.71) | (1.75) |

The sample size is 6980 households, t-statistics in parenthesis and *, **, *** indicates statistical significance at the 10%, 5% & 1% respectively.

## 2.9 Discussions and Concluding Remarks

Benazir Income Support Program is the largest-ever social safety net program in Pakistan's history in terms of allocated funds and its outreach. The program is currently in its 11th year. This chapter analysed the targeting performance of the program when identification of the poor was done through the local political community as agents of elected parliamentarians. Using Pakistan Social and Living Standards Measurement (PSLM) survey data for the year 2009-10, this chapter analysed the targeting error and benefit incidence of the program across Pakistan. The current research is unique as it is the first study that has measured BISP targeting performance using the provincially representative PSLM survey data set.

The results show that BISP benefits are mainly going to the poorest three quintiles and that the per capita annual income of the BISP recipients is substantially lower than that of the non-recipients. While there is a divide in income levels across rural and urban areas of Pakistan, no significant differences in income levels were found in the case of BISP recipients' households. However, it should be noted that the poorest quintile in rural areas received a significantly higher proportion of benefits as compared to the same quintile in urban areas. This is probably because it is easier for community political leaders to differentiate between the poorest and the poor in rural areas due to close community interactions and knowledge.

The targeting of households in Sindh and Punjab provinces was better than that in Balochistan and Khyber Pakhtunkhwa provinces, possibly due to the presence of higher levels of inequality in the former provinces (UNDP 2016b, Burki et al. 2015) . Research elsewhere suggests that targeting outcomes of anti-poverty programs are better in more unequal societies than in equal societies. Overall targeting shows that 84% of program benefits are going to the lowest three quintiles. The first, second and third income quintiles receive a share of 36%, 25% and 23% respectively. Six percent of program benefits are also going to the richest quintile.

On household characteristics, BISP recipient households have more female-headed households, larger family size, have more widowed women, and divorced female members as compared to non-recipient households. This seems to be due to the BISP project office instructions given to politicians to distribute the forms to widowed and divorced women. Similarly, BISP non-recipient households have significantly better indicators of employment and education as compared to those of BISP recipient households. The probit estimates confirmed the results of the benefit incidence analysis and found significant negative effects of per capita income on the probability of receiving a BISP grant. Compared to living in the Punjab province, the probability of selection into the program is significantly higher in KP and Sindh. The reason for the low coverage in Balochistan may be the ongoing Baloch insurgency, which may have put a limit on the movement of political workers. In Punjab, the coverage was low because the province was ruled by a party, which was in opposition to the central government thus shying away from distributing a form which had the picture of an opposition leader. Moreover, the Punjab government also introduced its own social safety net program to avoid distributing forms of BISP, which contains photos of their opposition political leader. Leakages of the program are more pronounced in the provinces of KP and Balochistan as compared to Punjab and Sindh.

With regard to household level characteristics, the results show that families where one or more member attains a higher education degree reduces the probability of selection into the program. Similarly, if a child in a household goes to a private school then the household's probability of selection into the program is reduced. Literature in Pakistan and elsewhere shows that both these variables are associated with higher incomes. Surprisingly, if a child in family works, their probability of selection into program reduces which shows that political leaders consider income earned by children as normal income. However, assets in the forms of durable assets reduces the chances of selection into the program.

To conclude, both benefit incidence analysis and probit estimates show that BISP benefits are mainly going to the lowest quintiles with some leakages to the richest quintiles. Political community leaders faced difficulties in differentiating between the poorest households and poor households thus leading to a substantial share of benefits going to the 2nd and 3rd quintile. It was found that parliamentarians and their political agents are supplying proportionately more forms to urban localities in comparison to rural localities. This is despite the fact that various monetary and non-monetary measures of poverty have always maintained that poverty in Pakistan is more in rural areas as compare to urban areas. Informational advantage in urban areas via-a-vis rural areas is enabling urban residents in reaching out to the parliamentarians to obtain a BISP form. As both rural and urban residents are competing to obtain forms from the same parliamentarian, rural residents are left out. This informational disadvantage in the rural areas also has a bearing on the overall targeting performance of the BISP program as our results show that BISP form distribution in rural areas was more pro-poor as compared to those in urban areas. While urban areas received proportionately more BISP forms, these were not as well-targeted as in rural areas, thus reducing the overall targeting performance of the program. There is also great variation across the provinces, which may be the result of various factors and which needs further investigation. Targeting of poor households in Sindh and Punjab was better than KP and Balochistan.

Our results from the analysis in this chapter shows that targeting performance of BISP program under community based targeting is quite propoor. BISP beneficiaries under the parliamentarians' targeting mechanism received funds from the BISP for a duration of 3 years, which were later stopped as program-targeting method was shifted to a more 'objective' criteria of poverty scorecard method. The shift was made on the recommendation of World Bank as the Bank also provided multiple Technical Assistance to government of Pakistan on BISP and social protection. Except for a small, unrepresentative study on the parliamentarian targeting performance of the program (World Bank 2009), there has been no rigorous study conducted to guide the policy of a shift from community-based targeting to poverty score targeting. Whether such a shift was warranted on the basis of targeting performance is discussed in somewhat more detail in chapter 5.

## Notes

[1] Please see (Nasir 2011)for a useful discussion on the costs & benefits of broadly targeted versus narrowly targeted anti-poverty programs

[2] Article 38 sub clause c, d & e of Chapter 2 of The Constitution of Pakistan. www.pakistani.org/pakistan/constitution/part2.ch2.html

[3] http://bisp.gov.pk/

[4] Those seven programs are Zakat, The Pakistan Bait-ul-mal, the workers welfare fund, employees social security institutions, the workers participation fund, wheat subsidy programs and Khushali Bank (Micro finance bank)

[5] World Bank http://data.worldbank.org/indicator/SI.POV.2DAY 7th February, 2013.

[6] There are several possible reasons for this variation, although the reasons are not entirely clear. For instance, it may be that some parliamentarians were not able to distribute their forms among people in their respective constituencies. In Balochistan, forms did not reach the expected beneficiaries due to ongoing insurgency in the province. In Punjab province, it was the opposition party in-charge of the provincial government thus resulting in low reach due to two reasons. First, there are news reports that the opposition political parties complained of not receiving their quota of forms. Second, those in the opposition who received the forms did not distribute it as the form contained a photo of Benazir Bhutto (a former Prime Minister), which the opposition party considered as promotion of its rival party. The forms may be distributed according to population share but due to screening out by BISP criteria some people were considered eligible and so grants given while others were rejected. Parliamentarians of one province may have distributed part of their share of forms in other provinces. The programs initial design did not stop parliamentarians from distributing forms outside their constituencies. This can happen because some political parties may have not elected representatives in some provinces and would want to distribute these forms among its supporters.

# 3 Political Capture in Targeting the BISP through Political Elites

## 3.1 Introduction

Across the globe, developing countries increasingly rely on narrow targeting for their poverty alleviation programs instead of universalism. Mkandawire (2005) discusses the forces behind the shift from universalism toward selectivity in using social policies to combat poverty in the developing countries. The most quoted factor behind this shift in the literature is the fiscal constraint in developing countries and the quest for reaching out to the poor more efficiently.

With the shift towards narrow targeting, a crucial aspect is the choice between a centralized or a decentralized system for delivering program benefits. A large number of poverty alleviation programs in developing countries have relied on a decentralized approach to target the poorest of the poor (Coady et al. 2004a, Alatas et al. 2012, Conning and Kevane 2002, Robertson et al. 2014). The merits of a decentralized system for delivering benefits, especially devolving the process of beneficiary identification, is based on certain assumptions. It is assumed that local administrators/elected politicians are able to target the poor more accurately as they are more embedded in the local community and are also subject to electoral pressures from local citizens who can monitor delivery closely as compared to a distant central authority (Stoeffler et al. 2016, Basurto et al. 2017, Bardhan and Mookherjee 2005, Galasso and Ravallion 2005, Alderman 2002). However, while a decentralized allocation mechanism may offer cost, informational and accountability advantages, it may also be prone to elite capture (Bardhan and Mookherjee 2005). Furthermore, decentralization may also fail to deliver services to the poor, particularly in developing countries, due to the lower capacity of local governments (Handa and Davis 2006, Robinson 2007). [1]

In the case of politically targeted and politically administered programs, there may also be political capture. As opposed to elite capture, where the non-poor may capture resources for their personal use, political capture is a phenomenon where politicians use government resources to buy votes and provide patronage. As argued in (Khemani 2010, Khemani 2013, Curto-Grau et al. 2012, Solé-Ollé and Sorribas-Navarro 2008, Chau et al. 2018), the risk of 'political capture', in anti-poverty programs, needs to be distinguished from that of 'elite capture' as analysed in (Bardhan and Mookherjee 2005, Bardhan and Mookherjee 2000). Elite capture is a phenomenon where funds are extracted by the non-poor from poverty-alleviation programs, while under political capture even if funds are better targeted towards poorer citizens, such targeting may be driven by a desire to buy votes in future elections or to reward loyal voters and, among others, may be characterized by pork-barrel projects.[2] In the case of political capture, even poor and traditionally disadvantaged voters may demand private goods from politicians and thus capture need not be restricted to the elite.

There is a large theoretical and empirical literature on the political capture of federal government grants where political factors play a prime role in the distribution of intra-governmental resources. The bulk of this literature concentrates on block grants distributed from the federal to the sub-federal governments (Boex and Martinez-Vazquez 2005, Grossman and Helpman 1996, Grossman 1994, Jarocińska 2010, Stein 1981, Wyatt 2013). Models by Cox and McCubbins (1986) and Dixit and Londregan (1998), using the median voter framework, argue that candidates of political parties contesting for elections make redistributive decisions in order to maximize the number of votes. Cox and McCubbins (1986) for example argue that political candidates who are risk averse will cater to their 'loyal' voters as they are 'well known' quantities.[3] On the other hand, Dixit and Londregan (1998) argue that candidates will focus their grant distribution efforts in areas where there is a greater concentration of 'swing' voters as such voters are more responsive to benefits due to their ideological indifference. A rather different strand of the literature focuses on the hypothesis that special interest groups 'politically capture' public resources and the distribution of resources has little to do with serving the interests of the median voter.[4] According to Boex and Martinez-Vazquez (2005) and Grossman and Helpman (1996), individuals with common interests form special interest groups and use their power to influence public policy in their favour. A similar explanation is put forward by Stein (1981) who argues that regions with powerful and influential leaders receive larger transfers as compared to those regions which do not have such leaders (grantsmanship hypothesis).[5] Wyatt (2013) on the other hand argues that in a clientelist political system, competition among political parties may not lead to the intensification of clientelism but instead political parties may dilute their clientelist strategy by the addition of some programmatic policies. Through these programmatic policies, these political parties offer political benefits to beneficiaries regardless of partisan affiliation.

In the case of Pakistan, the role of political patronage is well documented and several authors have argued that political parties and their governments at federal, provincial and local levels have been involved in tactical distribution of public resources (Mohmand 2014, Wilder 1999, Keefer et al. 2006, Hasnain 2008, Kitschelt and Singer 2009, Ali 2018).[6] The use of patronage received a special boost in 1985 when the military regime of Zia-ul-Haq initiated a special program that involved the allocation of funds to members of parliaments at federal and provincial levels which were expected to be spent on development schemes in their constituencies (Hasnain 2008). Since then, Pakistani politicians and military dictators have resorted to tactical distribution of resources to regions/constituencies where they expect to buy support. Since the 1980s, there have been regular reports in the electronic and print media that point out the role played by prime ministers, chief ministers, federal and provincial ministers and other MPs in using their special discretionary powers to allocate funds or jobs to districts and regions of their choice. While there are clear rules in the constitution of Pakistan that discourage the disproportionate, discretionary allocation of funds to specific regions, for the most part, institutions tasked with enforcement of rules are weak and thus these discretionary powers remain unchecked.[7]

Two strands of the literature are available on political capture of government resources. One strand of the theoretical and empirical literature concentrates on examining the role of political factors in influencing block grants distribution from the federal to the sub-federal governments. Another strand of the literature focuses on the political distribution of service delivery and resources at the village-municipality levels within a district by locally elected governments. Both these strands of literature, however, ignore how federal politicians play a role in within district/state distribution of funds. The unique project design of the Benazir Income Support Program (BISP) provides an opportunity to add to this literature by analysing distributions of federal funds by federal and provincial politicians among different localities within a district.

BISP went through two different design phases to target poor households in Pakistan. In the first phase during (2008-2011), constituency level politicians elected to provincial and federal governments from the districts were tasked with identifying poor households in their constituencies. In the second phase (2012 & onwards), the program targeted beneficiaries by using a Poverty Score Card (PSC) which was determined on the basis of a nation-wide census conducted in 2010-11. The current paper focuses on the outcomes of the targeting approach used during the first phase of the BISP program to examine the extent of political capture. The contribution of this paper is to provide empirical evidence on whether and the extent to which allocation of a decentralized anti-poverty program is driven by political considerations as opposed to equity considerations. While there is casual and anecdotal evidence that political factors play a role in allocating such resources in Pakistan, credible empirical evidence is limited. The chapter will also analyse differences in distribution outcomes for the ruling and opposition political parties and for local and non-local political parties.

The next section, 3.2, discusses the political context at the district level. Section 3.3 reviews theoretical debates and empirical findings on the politics of redistribution with a particular focus on developing countries. Section 3.4 sets out an analytical framework, which explores the potential effects of a mix of centralized objective criteria and decentralized subjective criteria on targeting. Section 3.5 discusses data sources and descriptive statistics. Section 3.6 discusses the empirical findings while the final section contains concluding remarks.

## 3.2 The Political context of District Swabi

Pakistan has four provinces with some Federally Administered Tribal Areas (FATA) and autonomous territories. Each province is divided into district administrative units and Swabi is one of 24 districts located in the province of Khyber Pakhtunkhwa in north-western Pakistan. According to the 1998 census, the total population of the district was 1.03 million and the district was the fifth largest in the province. Provisional figures from the 2017 census show that Swabi's population rose to 1.6 million in

2017. District Swabi is divided into 4 sub-districts, called Tehsils. Furthermore, these sub-districts are divided into 56 Union Councils (UCs), which is the lowest administrative unit and is responsible for delivering municipal services. Each local council in turn has 2 to 3 localities. For the analysis presented in this chapter, district Swabi is divided into 101 localities.

There are three different levels of governments in Pakistan – federal, provincial and local. Government at the lowest level is called Local Government (LG), which consists of three tiers, namely district, sub-district/tehsil and village/UC level government. Representatives of local government were elected in 2005 for a period of 5 years (2005-2010). After a gap of 5 years, local government representatives were again elected in 2015 for a period of 5 years. Between 2005-10, representatives of the local government were elected on a non-party basis. Political parties were not allowed to contest the elections with their own election symbols. This is typical of military regimes in Pakistan, as they strive for de-politicization of society. Thus, when the BISP was launched in 2008, a non-party based local government was governing at the local level. Municipalities at Village, Tehsils and Districts levels had elected representatives on a non-party basis. However, these representatives were tacitly supported by political parties. The mayors and the members of these UCs are important in the sense that they are well entrenched in the society at the street levels and are part of special interest groups (Mohmand and Cheema 2007).

While the elected setup, as described above, of the local government was in place in district Swabi at the time of the launch of the BISP, general elections to provincial and federal government were conducted in February 2008. At the federal level, the Pakistan People's Party (PPP) formed a coalition government while at the provincial level, the Awami National Party (ANP) formed a coalition government in Khyber Pakhtunkhwa. The election results in Swabi showed that ANP emerged as the leading party by winning one of two National Assembly seats and four out of six Provincial Assembly seats. ANP was the runner-up in the seats that it did not win.

As discussed earlier, BISP forms were distributed through MPAs, MNAs and Senators of respective districts. In 2008, there were two MNAs and six MPAs, who were elected based on adult suffrage of both men and women. Additionally, one senator, one MNA on women's reserved seat and two MPAs on women's reserved seats were also selected from district

Swabi to the Senate, National Assembly and Provincial assembly respectively. Therefore, in total, there were 12 elected representatives who received BISP forms from the project office of BISP to further distribute these forms in the district. Three MNAs and one senator received 8,000 forms each, while eight MPAs received 1,000 forms each. In total, there should be 40,000 BISP forms (enough to reach around 20 percent of total population of Swabi) available to be distributed in the district. However, elected representatives were not obliged to distribute forms only in their own districts.

## 3.3 Politics of Tactical Redistribution: Theories and Empirical Evidence

### 3.3.1 Equity and Efficiency Considerations

Normative theories of fiscal federalism which deal with the distribution of intergovernmental grants have urged that grants should be allocated on the basis of social welfare. This literature justifies these transfers on the basis of efficiency and equity concerns (Musgrave 1959, Oates 1972). These authors argue that intergovernmental transfers should be used to achieve fiscal equalization across different regions/states and to redistribute resources from richer to poorer regions. They also argue that funds should be transferred to support regions/states so that they may provide differential public goods as per the needs of their populations while ensuring an even distribution of basic services across all regions. This approach warrants that grants should be distributed based on certain formulas among states/local governments, which account for local needs and local fiscal capacity (Oates 1972). However, many scholars have recognized that often, what grantor governments 'ought to do' does not match what they 'actually do' (Solé-Ollé and Sorribas-Navarro 2008). In the last two decades, many studies have shown that federal grants are not consistent with normative considerations and have advanced theories (commonly known as second generation of theories) of fiscal federalism of political determinants (Oates 2005), which point towards the positive considerations of such transfers. A brief review of both the theoretical and empirical literature is presented in the subsequent sub-sections.

### 3.3.2 'Swing Voters' Hypothesis

While there is consensus that political factors do play an important role in the distribution of intergovernmental grants, there is considerable difference over which political factors play a leading role. Probably the first study that includes political variables into an allocation model is that of Wright (1974). Wright (1974) argues that interstate inequalities in per capita federal spending may be explained, in large part, as the result of a process of maximizing expected electoral votes. Based on an analysis of the New Deal spending in the US, Wright (1974) found that a 'political' model explained between 58.7% to 79.6% of the variation in per capita spending over the period 1933-1940 as compared to only 17% by the 'only economic' model. The model of 'political productivity' included variables such as electoral votes per capita, variability in the vote share of the incumbent government in the past elections and the predicted closeness (swing states) of the presidential elections. The model predicted that states with greater variability in vote share for the incumbent government and closeness of the presidential elections are favoured in the transfers of intergovernmental grants over other states.

A problem with the study of Wright (1974) was that it lacked a theoretical model to guide the researcher in terms of which political variables to include and what signs to expect (Johansson 2003). More elaborate theoretical models were presented in studies by Lindbeck and Weibull (1993, Lindbeck and Weibull (1987) as well as by Dixit and Londregan (1998), Dixit and Londregan (1996) and Dixit and Londregan (1995) which provide models with clear empirical implications.

For example, Dixit and Londregan (1996) argue that if political parties are approximately equal in their abilities to redistribute benefits once in office, then parties will tend to pursue similar strategies. The 'swing voter' outcome of an election will lead to redistributive politics that will favor three groups. That is: (i) groups with relatively many moderates whose relative indifference between the ideological programs of the two parties can be resolved by offers of redistributive benefits, (ii) groups that are relatively indifferent to party ideology relative to private consumption benefits, and (iii) low-income groups whose marginal utility of income is higher, making them more willing to compromise their political preferences for additional private consumption (Dixit and Londregan 1996). A similar conclusion was derived by Lindbeck and Weibull (1987), who argued that political parties will favour 'marginal voters' with weak party preferences given the heterogeneity in party preferences between groups. Both these models are different in their specification but the basic idea is the same - that is, political parties target those states for intergovernmental grants which have more 'swing voters' and thus have more competitive elections. Empirical research which supports the 'swing voters' hypothesis includes Case (2001) for Albania, Johansson (2003) and Dahlberg and Johansson (2002) for Sweden, Moser (2008) for Madagascar, Hirano (2011) for Japan, and Arulampalam et al. (2009) for India.

There are also studies which find mixed or no evidence for the hypothesis. For example in the case of the United States, Larcinese et al. (2010) found that states with many swing votes are not advantaged compared to states with more loyal voters, nor do 'battle ground' states attract more federal funds. Similarly, Menchaca (2012) found little evidence of higher federal spending in states that could swing the presidential election in the US. The author found little evidence to support the conventional belief that US presidents use federal spending to influence swing states. Notwithstanding these papers, the bulk of the empirical work in this strand of literature has found strong evidence of politicians encouraging greater spending in swing states/regions.

### 3.3.3 'Loyal Voters' Hypothesis

As opposed to the swing voters' hypothesis, another set of models gives a greater role to political parties targeting loyal voters in decision making regarding distributive politics. Cox and McCubbins (1986) model predicts that political patronage is the most visible and obvious redistributive strategy employed by politicians in a redistributive game. They divide the voters into three different groups from the political party's point of view, namely - the closest supporters, swing voters and opponents. They then equated risk-averse politicians to risk-averse investors and argued that risk-averse politicians will tend to over-invest in their closest supporters from the point of view of maximizing their expected vote. Similarly, risk-neutral parties will target swing voters while opponent groups are not likely to receive benefits. Thus, their model predicts that risk averse politicians will allocate funds to those states/regions where voters clearly support the incumbent party, which they term as 'core supporters'.

Empirical studies that confirm their model include Jarocińska (2010) for Russia and Finan (2004) for Brazil. Using data from Brazil's Chamber of Deputies, Finan (2004) found that a 10-percentage point increase in vote shares received in the previous election implies an expected increase of $ 75,174 in public works for a municipality during the electoral cycle.

### 3.3.4 Political Interest Group and Grantsmanship Hypothesis

A rather different theoretical and empirical literature argues that intergovernmental grants distributions are partly influenced by special interest politics. They emphasize that federal grants buy the support of 'political capital or resources' of the state (local) politicians and interest groups, which can be invested in efforts to further increase the support of state voters for federal politicians, that is, grant givers (Grossman and Helpman 1996, Grossman 1994). Grossman (1994) theorizes that other things being equal, grants go to those states where there are political agents with the most valuable political capital to sell. A rather similar framework was proposed by Stein (1981) and Rich (1989) who criticize the supply-side approach to inter-governmental distribution of grants. They propose to examine the question of grant allocation from a demand-side perspective – that is, focusing on the recipient jurisdictions. They argue that with an integrated approach, by linking both the demand-side and supply-side determinants of grant allocations, policy makers will be able to increase the use of grants and their equalization among needy and fiscally strained communities. The prediction of Stein's Grantsmanship hypothesis is that local/state governments with differential capacity to secure grants leads to an unequal transfers. As a corollary to this, one can argue that regions with influential and powerful local politicians (both elected and unelected) are able to extract more resources from non-formulae based grants as compared to other regions.

Grossman (1994) empirically tests his theoretical model by using a cross-sectional data of 49 states in US. The result show that the two variables used as proxies for 'special interest groups' increased grants to a state by between $65 to $151 per capita for every percentage point increase in the 'political capital' of the state. Similarly, each percentage point increase in a state legislature's democrat majority (a proxy of political groups) is worth between $0.75 and $5.08 per capita in additional grants to that state. They also conclude that over time, the importance of special interest groups has increased to political groups. Rich (1989) analysed allocation of six federal programs and showed that local level government exerts important influences on the distribution of federal grants. He also showed that distributional patterns of these grants vary over time and recommended focusing on a more disaggregated level at the recipient jurisdictions. Other empirical studies which support this explanation includes Sørensen (2003) for Norway. Borck and Owings (2003) consider a model where local government officials lobby the central government who in turn distributes grants based on local governments lobbying efforts. The authors found empirical support for their model and conclude that marginal cost of lobbying increases with the geographical and 'political' distance from the central government capital, which leads to a situation where grants decrease with a jurisdiction's distance from the capital.

In case of Pakistan, political competition among political parties may somehow compensate for weak institutions. Analysing municipal services at local level, Cheema et al. (2017) found that differences in access to government services is linked with density of party worker networks at the local level and that electoral competition faced by political representatives may compensate for the weak institutions and may lead to a fairer distribution of resources. Evaluating a micro-level setting in a district of rural Punjab, Mohmand (2014) found that political parties are indirectly connected with their voters mediated through local actors ranging from landlords and tribal leaders, to clientelist exchanges through brokers, kin groups and local party leaders. Looking at decentralization from a vote exchange perspective, Javed and Rehman (2016) found strong evidence for personalized politics and existence of clientelistic associations across Pakistan. Hasnain (2008) found that during the democratic era of 1988-1999, party systems were fragmented, factionalized and polarized thus creating incentives for direct benefits (patronage) weakening service delivery improvements. Majid and Memon (2017) construct measures of political inequality and political patronage and found a strong concave relationship between economic inequality and access to residential supply of natural gas across Pakistan. They also found that presence of strongmen is greatly associated with higher access to natural gas but it becomes insignificant once control for political competition. Similarly, Callen et al. (2018) found in a recent study on local government in Punjab that voters who elect a governing party politician (incumbent) receive higher quantity of services.

### 3.3.5 Voter turnout and 'Other' determinants of grants distribution

Another, somewhat different, strand of the theoretical and empirical literature highlights other determinants of intergovernmental distribution of federal grants. A theoretical model developed by Strömberg (2004), for example, argues that (i) government spending should be higher on groups where many have access to the media (ii) it should be higher on groups where more people vote and (iii) voter turnout should be higher in groups where many have access to the media. Their empirical results on New Deal spending in the 1930s, in the US, show that a one percentage point increase in the share of households with radios increases spending in a county by 0.61 percentage points. Of this, 0.54 percentage points is the direct effect while 0.07 percentage points is the indirect effect due to radio increasing voter turnout and voter-turnout increasing spending. Ansolabehere and Snyder Jr (2006) also found strong electoral incentives for political parties' to skew the distribution of funds to influence future election results as they found strong connections between turnout and government spending. Porto and Sanguinetti (2001) test the hypothesis in Argentina that the allocation of transfers among provincial states is strongly influenced by the geographical distribution of political representation within the National Congress. Their empirical results show that overrepresented provinces, both at the senate and at the lower chamber, attract, on average, higher resources from the national government compared to more populous and less represented states. Sørensen (2003) also found that disparities in the number of seats allocated to the national election districts influence the distribution of grants between municipalities and counties in Norway. Other studies Ishiyama (2010) and Treisman (1996) argue that federal transfers are higher for those states where regional discontent is higher and the federal politicians want to 'appease' the local population to avoid conflict.

## 3.4 An Analytical Framework

Most of the theoretical and empirical literature discussed in the previous section on political determinants of inter-governmental transfers focuses on block grants distributed from the centre/federal government to the provinces/states. This literature examines the allocation of inter-governmental grants and the influence of various factors, including normative factors such as efficiency and equity, pork-barrel politics and voter choice arguments, special interest politics and other important political factors. The large empirical evidence suggests that equity and efficiency considerations play a limited role while various political factors explain the distribution of these grants. Drawing lessons from this literature, researchers and policy makers then suggest constitutional rules to devise a formula-based mechanism of inter-governmental grant distributions to restrict the extent to which political factors can negatively affect equitable resource distributions to state/provincial level.

As discussed above, while there is a large literature on inter-governmental (federal to state) grant distribution, there is very little empirical evidence on how federal grants are distributed within a state/province among different districts, sub-districts, municipalities and localities. Some notable exceptions do exist where researchers have studied the determinants of grant allocation from the federal government to the district or municipality level (Alderman 2002, Bardhan 2002, Bardhan and Mookherjee 2002, Glasso and Ravallion 2005, Hasnain 2008, Khemani 2010). However, these studies do not consider the political determinants of inter-locality distribution but tend to compare centralized and decentralized regimes regarding service delivery and elite capture. Thus, most of the previous work concentrates mainly on the decentralization aspects of these grants at the lower tier of government, mainly at municipality level and the comparison of relative capture of centralized (national) versus decentralized (local) programs.

The current paper adopts the analytical framework of the studies conducted on the distributional impact of inter-governmental block grants allocations and its political determinants but in a departure from the literature, it focuses on the local level and examines the role of various economic and political factors in determining the inter-locality distribution of the BISP.

Specifically, the aim is to examine the role of different variables in explaining the distribution of BISP forms across different localities in district Swabi while controlling for various socio-economic indicators of the localities. These socio-economic indicators serve as a proxy for the backwardness and poverty of the localities. Normative theorists argue that localities which are relatively poor (on social and economic indicators), should receive a greater share as compared to those that are relatively better off. This, however, does not mean that the grants distributed will reach the poor in these different localities. This will only indicate the responsiveness of politicians to the relative poverty of a locality as compared to their responsiveness to political variables.

To examine whether the spatial distribution of BISP forms in district Swabi is biased towards poorer localities or towards localities with greater 'political power', we estimate three variants of the following OLS regression. Consider the equation below,

$$Forms_i = \alpha + \beta\ Population_i + \tau X_i + \gamma\ Urban\ _i + \propto Turnout_i + \ \pi ImportantPolitician_i + \mu Loyal_i + \theta Swing_i + \varepsilon_i \qquad (1),$$

where, the dependent variable *Forms* is the number of BISP forms distributed across locality (*i*) by representatives of political parties in district Swabi. Population indicates the population size of the locality, *X* is a matrix of four explanatory variables controlling for socio-economic status of the locality. It includes the share of population that has ever attended school, share of mud houses, share of houses with potable water and share of houses with electricity in the localities. The variable *Urban* indicates whether the location is urban or rural. Two different definitions are used, as discussed in detail in the section on variables. The first variant of *Urban* in equation (1) uses the census rural/urban location while the second variant divides the localities into four sub-categories, instead of two, depending on the level of urbanization in the locality.

Motivated by a reading of the literature and knowledge of the local context, the last four variables included in the equation are political variables capturing political factors that may drive the distribution of BISP forms across localities.

Turnout is the male turnout in a locality in an election which was conducted just prior to the introduction of the BISP program. General elections for the federal and provincial governments were conducted in February 2008, which were being held after years of dictatorial rule. BISP was announced by the new federal coalition government led by the PPP, which emerged as the single largest political party at the federal level in the 2008 elections. A budget for the BISP was earmarked in June 2008 and the program was launched in October 2008. Inspired by the literature presented in section 3.3.5, voter turnout is included in the equation. A priori, a positive sign is expected as the larger the turn out the more likely it is that politicians will respond to politically active localities as opposed to localities which don't participate actively in voting. Instead of using overall turnout, male turnout is used as there were localities (38 of 101) where females were not allowed to vote.[8] Even where women were allowed to vote, very few women came out to vote on election day. For the 101 localities in Swabi, voter turnout for males was 52.64% while female voter turnout was 16.01%.

'Important Politician' is a dummy variable capturing the presence of an important politician in or close to a locality. Three different proxies were used to capture this variable in three different specifications. First, we use a broad definition of an important politician (Close Politician) where an important politician is one who is a member of the provincial assembly (MPA), national assembly (MNA) or the Pakistani Senate (Senator). This definition of important politician also includes runner-ups to MPA and MNA seats and those politicians who are based in the district and hold important positions in the organizational setup of their respective parties at district, provincial or national level. They usually head the party political machine at the district, tehsil or locality level to which elected members of parliaments are accountable. This variable also includes important elites (both political and moneyed) who are significant movers/influencers and form special interest groups around important political leaders. In the second specification, we use a narrower definition that includes only the MPAs, MNAs, Senators or runner-up [MPA/MNA] in the previous election as important politicians. Important political and moneyed elites in the previous specifications is drop in this definition. In the third, the most restrictive specification, we use only the incumbent MPA, MNA or Senator [Incumbent politician] as important politician. This category includes only those politicians who actually 'own' the BISP forms as they directly receive these forms from the BISP office. The variable of 'Important Politician' enters the specification as a dummy variable - that is, the variable takes on a value one if such a politician lives in the locality and 0 otherwise. These three different definitions of an important politician will help us understand the political dynamics at the district level as theorised in section 3.3.4 about special interest groups and the grantsmanship hypothesis.

The variable *Loyal* indicates a locality where the winning margin in the locality for any incumbent candidate is greater than +10% while a *Disloyal* locality is that where the losing margin for any incumbent politician is larger than -10%. On the other hand, the *Swing* variable denotes a locality where the competition is close enough and the winning/losing margin is between +10% and -10%. Besides loyal/swing categorization, we also include a variable of absolute margins of Win/Loss in a locality in the previous election.

To examine variation across political parties, equation 1 was also estimated for the forms distributed by the ruling party (ANP) and the opposition parties combined (non-ANP). ANP distributed around 43% of total forms while non-ANP parties distributed the remaining forms. We also make another distinction between forms which are distributed by local parliamentarians or non-local parliamentarians and run two different specifications of equation 1. Local politicians are those who are winning candidates from the district and distributed their forms in district Swabi. Non-local politicians are those who won their seats from other districts but their political machines were able to distribute a share of their forms in district Swabi. It will be interesting to see whether there are any significant differences in the distribution of forms as local parliamentarians can follow up forms issued with his/her name as against those parliamentarians who solely rely on their party machine in a 'remote' district. Local parliamentarians distributed around 80% of the BISP forms in district Swabi while the remaining forms were distributed by the party activists of the non-local parliamentarians.

A priori, if politicians take into account the socio-economic characteristics of a locality, then backward localities should receive a greater share of the forms as compared to relatively rich localities. However, if political factors prevail then the distribution of forms across localities may have little to do with the socio-economic traits of the localities. As discussed in the theoretical section, there can be multiple political factors in play. If politicians value localities with larger turnouts on election day then the variable which captures turnout should have a positive effect on allocation of forms. If special interest groups are active in the district then localities that are closest to the incumbents are more likely to be rewarded. If the swing voter hypothesis holds then politicians may be expected to distribute more forms in swing localities while if the loyal voter hypothesis holds they may be expected to favour localities where they have won elections with big margins.

## 3.5 Data Sources and Descriptive Statistics

### 3.5.1 Data Sources

The data for the empirical analysis in this paper comes from three different sources.

*Data on BISP Forms Distribution*

The Project office of the Benazir Income Support Program (BISP) provided data on the number of BISP forms distributed by politicians in different localities of district Swabi in October 2008. Swabi district is divided into four sub-districts (Tehsils) and is further divided into 56 Union Councils (UCs). On average, UCs have a population of 18,336 people (census 1998) with an average voting population of 10,208, according to the 2008 election commission data. Each UC consists of localities each of which has a local government setup in 2008, which provides municipal services to its people. When these forms were processed in the project office of the BISP for eligibility, they were categorized in three different categories of eligible, non-eligible and withheld forms. These categories were made on the basis of the eligibility criteria designed for the program. The forms with withheld status are those whose application forms were not accompanied by relevant documents such as CNIC or lack of signature of the parliamentarian or were not authorized by a member of the UC.

*Data on Election Results & Important Politicians*

Data on election results in district Swabi was obtained from the website of the Election Commission of Pakistan (ECP)[9] and processed to suit the current research. It contains authentic and final data on the total electorate in different localities and the number of votes received by the candidates of different political parties in both the national and provincial elections, which were held in February 2008. The data also contains the names of localities where different party members live, which shows that while some localities have more contestants in the general elections there are also localities that have no contestants in the general election. Data on important politicians, as discussed earlier, was constructed from the 2008 election results combined with focus group discussion with political parties in their party offices. In total, we held 41 focus group discussions with 11 parliamentarians, 4 district presidents and other members of 4 different political parties in their party offices, 20 local government members including UC Nazims (Mayor). We also held discussions with 6 runner-up candidates. All these FGDs were conducted in order to understand the political atmosphere of the district and of different localities within district, party machines of various political parties and the system of political patronage, and how they respond to their vote base.

#### *Census Data on District Swabi*

The census data on district Swabi was obtained from the Pakistan Bureau of Statistics (PBS). The data includes the total population with male and female share as per the last census conducted in 1998.[10] It also includes information on the share of the rural/urban population, literacy ratios, and primary and secondary school enrolments, housing characteristics, housing facilities, and drinking water availability in each locality. Besides census bifurcation of regions into urban and rural, which was based on the 1998 census, a new variable of "urbanness" was constructed by the researcher. This was done in order to obtain a more recent measure of urbanization. Localities were divided into very rural, rural, urban and very urban based on more recently available data (discussed in subsequent section).

### 3.5.2 Data Description

Table 3.1 provide summary descriptive statistics of the dependent and explanatory variables used in the OLS regressions. Part 1 of the table provides summary statistics regarding the dependent variables. BISP Forms were divided into three different categories, namely eligible, non-eligible and withheld. According to data obtained from the BISP project office, the total forms distributed in district Swabi by all parliamentarian amounted to 35,132 with an average of 348 forms per locality. If parliamentarians had been forced to distribute the forms only in their own constituencies then the total forms distributed should have been 40,000 in district Swabi as per allocation of forms to parliamentarians of Swabi. There are multiple reasons for this shortfall. One provincial assembly member did not distribute a single form out of his 1,000 quota of allotted forms as he was out of the country for an extended period. Furthermore, four incumbent politicians who were residents of the district had been selected on special seats for women or selected as Senators and thus represented the entire province and not just a district alone. These four politicians from district Swabi distributed a part of their forms in other districts through their political party machines. Similarly, many politicians from other districts distributed a part of their allotted forms in district Swabi, which is discussed later in the section.

After the distribution of these forms by parliamentarians, filled-in forms reached the central office of the BISP secretariat from all over Pakistan. These forms were then processed for data verification by an external government agency (namely NADRA) which has records on every individual who has been issued a Computerized National Identity Card (CNIC). Based on initial screening, incomplete forms submitted by the applicants for grants were categorized as withheld. Incomplete forms are those that were not signed by the applicant or by the local councillor or not accompanied with CNIC of the applicant. A total of 4,188 application forms (12% of the total forms) were put in this category with an average of 42 forms per locality in district Swabi. The remaining completed forms were then scrutinized on the objective criteria provided to the National Database Registration Authority (NADRA) by the BISP office and so the applications forms were categorized either as eligible or as not eligible. A total of 22,888 forms (65% of the total forms) were categorized as eligible from district Swabi with a mean number of 227 forms per locality while 8,056 forms (23 % of the total forms), were categorized as not-eligible with an average of 80 forms per locality.

In order to explain inter-locality variation in the allocation of BISP forms, we also differentiate the forms distributed by ANP[11] and non-ANP political parties. ANP distributed 15,122 (43% of the total) forms in the district while the remaining 20,010 (57% of the total) forms were distributed by all other political parties. These other parties also include other political parties who distributed forms in the district while having no elected representative from the district. Similarly, we distinguish the forms distributed by local and non-local parliamentarians. A total of 28, 202 (80% of total) BISP forms were distributed by parliamentarians who were elected/selected from district Swabi (local) while the remaining 6,930 (20% of total) forms were distributed by parliamentarians who did not belong to district Swabi. Forms of these non-local parliamentarians were distributed by their party political machines in the district.

Part 2 of table 3.1 provides descriptive statistics of the explanatory variables used in the regression analysis. The district's population of over 1 million lives in 101 localities with an average population of 10,166 persons per locality. In our OLS regressions, we control for population in all our specifications. For the education level of a locality, we use the variable 'share of population ever went to school' as this also controls for the supply side of school availability. The other variable 'literacy ratio' is very broad and includes people who may not have gone to school. There is a correlation of 95% between the two variables.

We include three explanatory variables related to the housing infrastructure as a proxy for the poverty of a locality. The house structures in the district are categorized into three different categories, namely concrete, semi-concrete and mud houses. We use the share of mud houses in a locality as a proxy for the poverty status of a locality. The average share of mud houses in a locality is 32.7% with a standard deviation of 18.6, while there are localities where the share of housing structure made of mud is as high as 79%. The other variable included in the analysis is share of houses in the locality which have potable water. The average share of houses with potable water is 10.8 % with a standard deviation of 14.8. There are localities in the district where the share of houses with potable water is 77.7 %. The final variable in this category is share of houses with electricity. Localities across district Swabi are mostly electrified with an average of 76% of houses having electricity.

We use two different variables for the urbanization of a locality. The first variable, urban census, is taken from the census of 1998 which categorizes localities into rural/urban location. According to this measure, only 9 localities, accounting for 17% of the district population, are categorized as urban. However, this categorization was done in 1998 so we constructed another measure, which caters for developments in the last decade. We created a variable that took on four different values on the basis of the degree of urbanization. The information was collected from key informants in these localities. These levels of urbanization include proximity to big markets, banks and commercial centres, municipality head office, schools, colleges, health centres/hospitals, central and provincial government offices and occupational/income sources of the people in the area. According to these characteristics, the locations where urbanization is highest were named as 'Very Urban' and that includes 7 localities where 15.7 % of the population resides. Very urban areas are those localities which are built around main markets where both government and private health/education facilities are concentrated. These are areas where commercial banks, insurance companies, transport infrastructure, public courts and other government offices are located. The second category is 'Urban" and includes 24 localities comprising 37.3 % of the total. These are mainly semi-urban localities that lie close to the very urban areas. These localities are within a 5 km radius of very urban areas and can access the facilities of these very urban areas. The third category is 'Rural' which includes 38 localities and accounts for 34 % of the total population of the district. These areas are on the outskirts of very urban localities and at a distance of 5km to 10km radius. These areas do not have access to private health or educational facilities and are far away from the highly urban centres. The main income source in these rural areas is agriculture and its trade. The last category is 'Highly Rural' which includes 32 localities where 13% of the population resides. These are far-flung areas which are at a distance of more than 10 km from the urban centres. Accessibility to these areas is highly restricted and time consuming with very little means of transport.

The last category of explanatory variables consists of political variables. For voter turnout, three variables were considered, that is, male turnout, female turnout and total turnout. However, the variable included in the final analysis is the male turnout in the locality. The female turnout is quite volatile and depends on exogenous factors such as consensus among the political figures of a locality on whether women should be allowed to vote or not. Though women are legally eligible to vote, in as many as 38 localities women did not vote at all (see table 3.1). The overall female voter turnout was 16.01% which is substantially lower than the male turnout of 52.64%.

To capture the presence of an 'important politician' in a locality we explored three different possibilities. The first proxy of 'important politician' is the presence of an 'incumbent politician' in a locality. These are politicians who have won or been selected for the provincial/national assemblies or for the senate of Pakistan and reside in a locality which serves as their stronghold in term of vote bank and support. They directly received a quota of BISP forms from the program management office and were entrusted with the distribution of these forms in their respective constituencies. There are 11 such localities where 12 incumbents of the district reside (there are two incumbents in one particular locality). A broader indicator of "important politician" is the presence of an MPA, MNA, and

Senator with the addition of those contestants who won a sizeable number of votes in the last election. We took those contestants who polled at least 1,000 votes in the previous elections. On average, this figure of one thousand votes is around 10% of the votes polled by a winning candidate. However, these contestants have no direct access to BISP forms they have strong connections within their respective political parties and so indirectly receive and distribute forms in their respective constituencies. The fact that they were given a party ticket by their respective parties shows their influence both in the party and in their localities. There are 25 localities where either the MNA or MPA or an important contestant resides. The broadest definition of "important politician" includes 39 localities. This category includes political figures who are important in the district, provincial or national political scene. In addition to MPAs, MNAs & Senators [the incumbents], these political figures are leaders of different political parties who have influence in their respective political parties. They are in party positions at the district, sub-district and union council levels and belong to those political parties, which have an electoral vote bank in district Swabi. It also includes those important persons who contribute resources to the party candidates during election campaigns. These political and economic elite in turn have their own circles in their respective areas where they have influence over a large number of people through their *biradari*[12] networks. These are also individuals who can use local resources in their own localities in terms of the provision of services from three different tiers of government. These typical patron-client factions are thus an important source of the power of a locality in terms of any resource redistribution and are well-known to the people in a locality. A significant coefficient with positive signs for any of these three measures of 'important politician' implies that political elites prefer their own localities and allocate resources in favour of their own strongholds.

Lastly, to test whether politicians favour swing or loyal localities in the inter-locality distribution of BISP forms, we created two different set of variables based on the last general election results. We follow previous research, such as, Johansson (2003), Case (2001), Dahlberg and Johansson (2002) to construct these variables and used closeness in the last election as a proxy for loyal or swing localities. As there are many candidates running for the same parliamentary seat, we used the margin of victory between the winner and the closest runner up to define the variable of interest. Thus, localities where the margin of victory in elections for a National

 

Assembly seat was less than 10 percent were classified as swing localities and when the margin was greater than 10 percentage points the locality was classified as loyal or disloyal locality. Overall, there are 32 localities where the election is close and the margin of victory is less than 10 percentage points, while the remaining 69 localities have a higher margin of either a win or a loss. A continuous variable of the absolute margin of win or loss is also used to proxy for swing or loyal localities.

 

***Table 3.1***

*Full Sample (101 Localities) Descriptive Statistics at Locality Level*

| *Variable Name* | *Variable description* | *Mean* | *Std. Dev.* | *Min* | *Max* | *total* |
|---|---|---|---|---|---|---|
| **Part 1: Number of BISP Forms distributed in a locality [Dependent Variables]** | | | | | | |
| Total Forms | All forms distributed by all politicians | 347.8 | 343.3 | 27 | 1662 | 35132 |
| Eligible Forms | Forms eligible for BISP cash grants | 226.6 | 217.8 | 16 | 952 | 22888 |
| Not Eligible Forms | Forms not eligible for BISP cash grants | 79.8 | 78.3 | 1 | 320 | 8056 |
| Withheld Forms | Forms withheld for BISP cash grants | 41.5 | 97.4 | 0 | 941 | 4188 |
| ANP Forms | All forms distributed by ANP politicians | 149.7 | 159.6 | 11 | 813 | 15122 |
| Non-ANP Forms | All forms distributed by Non-ANP politicians | 198.1 | 247.6 | 0 | 1363 | 20010 |
| Local Politicians Forms | All forms distributed by Local politicians | 279.2 | 276.4 | 21 | 1329 | 28202 |
| Non-Local Politicians Forms | All forms distributed by Non-local politicians | 68.6 | 154.8 | 0 | 1334 | 6930 |
| **Part 2: Explanatory Variables** | | | | | | |
| **A. Population, Housing Conditions and Urbanization** | | | | | | |
| Population | Total Population | 10166 | 7957 | 697 | 32057 | 1026804 |
| School | share of population ever attended school | 17.0 | 6.1 | 4.8 | 32.1 | |
| Mud House | Share of Mud houses in a locality | 32.7 | 18.6 | 0.0 | 79.0 | |
| Potable water | Share of houses with potable water in locality | 10.8 | 14.9 | 0.0 | 77.7 | |
| Electricity | Share of houses with electricity in a locality | 76.1 | 22.3 | 0.0 | 98.0 | |
| Urban Census | Urban as per 1998 Census | 0.09 | 0.3 | 0.0 | 1.0 | |
| Very Urban | Very Urban [own calculations] | 0.07 | 0.3 | 0.0 | 1.0 | |
| Semi Urban | Semi Urban [own calculations] | 0.24 | 0.4 | 0.0 | 1.0 | |
| Rural | Rural [own calculations] | 0.38 | 0.5 | 0.0 | 1.0 | |
| Very Rural | Very Rural [own calculations] | 0.32 | 0.50 | 0.00 | 1.0 | |
| **B. Political Variables** | | | | | | |
| Male Turn Out | Male election turn out in 2008 elections | 52.60 | 7.80 | 35.90 | 77.60 | |
| Female Turn Out | Female election turn out in 2008 elections | 16.01 | 14.55 | 0.00 | 46.9 | |
| Total Turn Out | Total election turn out in 2008 elections | 38.11 | 7.33 | 23.6 | 61.3 | |
| Whether Female vote? | Whether female vote in a locality | 0.62 | 0.49 | 0.00 | 1.00 | 63 |
| Close Politician | Close Politician living in a locality | 0.39 | 0.49 | 0.00 | 1.00 | |
| MPA/MNA/Senator/Runner-Up | MNAs/MPAs/Senators/runner up | 0.25 | 0.43 | 0.00 | 1.00 | |
| Incumbent politician | Incumbent MNAs/MPAs/Senators | 0.11 | 0.31 | 0.00 | 1.00 | |
| Loyal Localities | Loyal Localities | 0.32 | 0.47 | 0.00 | 1.00 | |
| Swing Localities | Swing Localities | 0.32 | 0.47 | 0.00 | 1.00 | |
| Disloyal Localities | Disloyal Localities | 0.37 | 0.48 | 0.00 | 1.00 | |
| Winning Margins | Absolute Winning Margins | 0.19 | 0.14 | 0.00 | 0.69 | |

## 3.6 Empirical Findings and Discussions

OLS estimates of equation 1 based on different specifications are reported in tables 3.2 to 3.5. As discussed in the previous sections, the explanatory variables consist of two groups where the first group is a set of control variables to proxy for the poverty/backwardness of a locality while the second set consists of political variables. If normative considerations are important then the distribution of BISP forms should be concentrated in areas where poverty is more pronounced. However, if political considerations are important then political variables will dominate the distribution of forms.

Results in column 1, table 3.2, are based on the census definition of rural-urban while results in column 2 are based on the 4-part definition of rural-urban locations. Columns 3 and 4 adds voter turnout as our first political variable in the explanation of forms distribution within different localities of the district.

Column 1 of table 3.2 shows mixed results with regard to the effects of socio-economic variables on the distribution of forms. On the one hand, an increase in the availability of potable water in a locality by 1 percent is associated with a reduction of 2 forms for the locality while an increase in electrification is associated with an increase in the receipt of forms. Both the relationships are statistically significant. On the other hand, literacy rates and share of mud houses in a locality has no impact on the distribution of BISP forms. The results are not sensitive to changes in the definition of rural-urban localities (column 2 of table 3.2). The variable that figures most prominently in these first two specifications is the urban-ness of a locality. Using the census definition of rural-urban, urban localities receive 292 more BISP forms than the rural localities indicating politicians' bias towards the urban centres. Similarly, based on the 4-part definition of rural-urban localities, we find that the most urbanized locality gets 469 more forms as compared to the most rural locality. The explanatory power of the equation increases from 65% in specification 1 to 70% in specification 2. The large effect of living in an urban area is consistent with the idea of greater information access and closer reach to politicians amongst the urban populace. It is consistent with the theoretical models developed by Strömberg (2004), Ansolabehere and Snyder Jr (2006) which predict this result that localities with greater access to information are more likely to have greater government spending.

Results of adding voter turnout to the equation are reported in columns 3 and 4 of table 3.2. In both specifications, voter turnout enters significantly. In terms of magnitude, a one percent increase in voter turnout is associated with an allocation of 6 more forms. In other words, an increase in voter participation by one standard deviation (about 8%) leads to the allocation of 48 forms or about a 14% increase in the number of forms (48/348). Voter turnout, which signals greater political involvement, does seem to be translating into greater access to social protection resources. This is consistent with the implications of Strömberg's (2004) theoretical model which predicts that government spending will be higher in groups where more people vote as politicians have a stronger incentive to spend money in areas where voter turnout is higher with a view to influence future election results.

***Table 3.2***
*Regression Results for Socio-Economic Determinants of BISP Forms Distribution [All Forms with Census & 4-part Definition of Rural/Urban]*

| Variables | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Socio-Economic Factors** | | | | |
| Population | 0.02*** | 0.02*** | 0.03*** | 0.02*** |
| | (6.19) | (4.83) | (6.71) | (5.16) |
| School | 1.26 | -1.29 | 2.82 | 0.37 |
| | (0.3) | (-0.31) | (0.67) | (0.09) |
| Mud House | -1.11 | -0.59 | -1.36* | -0.83 |
| | (-1.47) | (-0.84) | (-1.66) | (-1.15) |
| Potable Water | -2.35** | -2.40** | -1.77 | -1.93* |
| | (-2.17) | (-2.52) | (-1.44) | (-1.81) |
| Electricity | 1.14* | 1.32** | 0.98 | 1.24** |
| | (1.95) | (2.36) | (1.47) | (2.04) |
| Urban [Census] | 292.47** | | 299.76** | |
| | (2.18) | | (2.33) | |
| Very Urban | | 469.21*** | | 448.01*** |
| | | (2.9) | | (2.77) |
| Urban | | 170.73** | | 157.09** |
| | | (2.52) | | (2.19) |
| Rural | | -38.59 | | -52.25 |
| | | (-1.36) | | (-1.65) |
| **Political Factors** | | | | |
| Turnout | | | 5.96** | 5.34* |
| | | | (2.12) | (1.78) |
| **Constant** | 15.16 | 46.51 | -315.32* | -251.9 |
| | (0.3) | (0.83) | (-1.92) | (-1.43) |
| **R-squared** | 0.65 | 0.7 | 0.66 | 0.71 |
| Number of Observations (localities) | 101 | 101 | 101 | 101 |

Notes: The dependent variable in the specification from 1-2 is the number of all forms distributed by All parliamentarians per locality in District Swabi. The *t*-ratios with heteroscedasticity-robust errors are given in parenthesis. * = significance at 10% level (two-tailed test), ** = significance at 5% level (two-tailed test), *** = significance at 1% level (two-tailed test).

Additional political variables are added to the next set of specifications. Results of four different specifications with the census definition of rural-urban distinction are reported in table 3.3, while table 3.4 present results with the alternative definition of rural-urban locations.

To start with, column 1 of table 3.3 shows estimation results where the specification includes the broadest definition of 'presence of an important politician' – labelled as 'close politician' in the table. To reiterate, this includes incumbent politicians, elected MNAs/MPAs/Senators, those politicians who received a competitive share of votes in the previous elections and important political figures who may not have contested elections but have a strong influence in political parties. The results suggest a substantial role for the presence of a 'close politician' in a locality and if the locality is a swing locality. Controlling for population and other poverty related locality specific variables, a locality where a close politician resides gets an extra 191 forms (on average) as compared to a locality which does not have such close politicians. The result further shows that besides rewarding their own locality/constituency, politicians award swing localities with more forms while the coefficient of the variable representing loyal localities is insignificant as compared to the control group of disloyal localities. A swing locality receives 80 more BISP forms from politicians as compared to a disloyal locality. The effect of voter turnout vanishes when the presence of a 'close politician' is included in specification one. With regard to other controls, the coefficient on 'urban' remains large and significant showing concentration of BISP form allocation in urban centres. Controlling for other factors, an urban locality receives, on average, 273 more forms than a rural locality. This concentration of BISP forms in urban areas, as discussed earlier, is perhaps the result of better information about the program intervention in urban areas as compared to rural areas. On normative grounds, BISP forms concentration should have been higher in rural localities as compare to urban localities as poverty in rural areas is almost twice that in urban areas.[13]

In the next specification reported in column 2 of table 3.3, a more stringent definition of 'important politician' is adopted where a dummy variable indicates the local presence of an MPA, MNA, or a close runner up in the 2008 general election. The regression results show that this variable does not exert a statistically significant effect on the distribution of forms and the explanatory power of the model drops from 73 to 68 percent. The lack of effect may be attributed to the inclusion of the runner-up in the last elections in the definition of important politician. To test this, runners up to MPAs and MNAs were dropped (in the third specification, column 3 in table 3.3) and a new variable that is based only on incumbent politicians is used as a proxy for important politician. The results are reported in column 3 of table 3.3. It show that the coefficient on this new proxy for 'important politician' is larger and is statistically significant. The effect of an "important politician" based on this specification is much larger than the other two and shows that localities with incumbent politicians received 410 more BISP forms (on average) than localities where there are no such politicians. Clearly, incumbent politicians are using their power and influence to allocate resources to the localities where they reside. In both, the second and third specifications, the coefficients on loyal or swing localities is insignificant. In the fourth specification (column 4 of table 3.3) a variable which captures the absolute winning margins is used instead of loyal and swing dummies. The coefficient on this new variable is statistically significant and has a negative sign indicating that higher the margin of winning or losing the lower the number of forms distributed to that locality. This is consistent with the earlier result (column 1 of table 3.3) that politicians allocate more forms to swing localities. In short, those localities where they are more likely to win or lose resoundingly are less likely to be favoured as compared to swing localities.

***Table 3.3***
*Regression Results for Political Determinants of BISP Forms Distribution*
*[All Forms with Census Definition of Rural/Urban]*

| Variables | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Socio-economic Factors** | | | | |
| Population | 0.02*** | 0.02*** | 0.02*** | 0.02*** |
| | (7.46) | (5.43) | (6.60) | (6.15) |
| School | 0.76 | 2.61 | 3.7 | 3.36 |
| | (0.19) | (0.56) | (0.97) | (0.89) |
| Mud House | -0.51 | -1.05 | -0.99 | -1.25* |
| | (-0.64) | (-1.29) | (-1.46) | (-1.76) |
| Potable Water | -2.00* | -2.11* | -1.59 | -1.56 |
| | (-1.69) | (-1.75) | (-1.52) | (-1.52) |
| Electricity | 0.16 | 0.87 | 1.05* | 1.48** |
| | (0.25) | (1.30) | (1.74) | (2.39) |
| Urban [Census] | 273.01** | 269.56** | 184.36** | 181.25** |
| | (2.44) | (2.33) | (2.38) | (2.37) |
| **Political Factors** | | | | |
| Turnout | 3.84 | 5.83** | 4.09* | 3.4 |
| | (1.49) | (2.05) | (1.78) | (1.44) |
| Presence of Important Politician | | | | |
| Close politician | 190.74*** | | | |
| | (4.43) | | | |
| MPA/ MNA/ Senator/ Runner UP | | 107.19 | | |
| | | (1.39) | | |
| Incumbents | | | 409.81*** | 419.91*** |
| | | | (4.77) | (4.95) |
| Loyal Localities | 78.25 | 66.53 | 18.67 | |
| | (1.63) | (1.33) | (0.50) | |
| Swing Localities | 80.09* | 77.76 | 52.58 | |
| | (1.74) | (1.56) | (1.27) | |
| Absolute Winning Margins | | | | -249.9** |
| | | | | (-2.14) |
| **Constant** | -240.01 | -352.5** | -267.1* | -166.01 |
| | (-1.52) | (-2.04) | (-1.89) | (-1.13) |
| **R-squared** | 0.73 | 0.68 | 0.78 | 0.79 |
| **Number of Observations (Localities)** | **101** | **101** | **101** | **101** |

Notes: The dependent variable is the number of all forms distributed by all parliaments per locality in District Swabi. The *t*-ratios with heteroscedasticity-robust are given in parenthesis. * = significance at 10% level (two-tailed test), ** = significance at 5% level (two-tailed test), *** = significance at 1% level (two-tailed test).

Table 3.4 presents estimates where the specifications are based on using the alternative definition of rural-urban locations. The results are robust and similar to those presented in table 3.3. The estimates continue to highlight that living in an urban location, perhaps due to informational advantages and access to political party offices/officials lead to a higher allocation of BISP forms as compared to residing in rural areas. Furthermore, important politicians, especially incumbent politicians, tend to pay greater attention to their own localities and a normative consideration of equity and efficiency appear to be less important in determining form allocation.

Voter turnout is statistically significant as a determinant of BISP forms in some of the specifications. However, the effect is not very large. These patterns suggests that patron-client relationships, as represented by 'important politician', is more influential in determining access to resources as compared to political awareness of people manifested through showing up to vote on election day. With regard to swing or loyal localities, the results in table 3.4 show that politicians are more responsive to the localities where previous elections were closely contested. In all four specifications, being a swing locality works towards increasing access to forms. Depending on the specification, the effect ranges from 86 to 106 forms. This is a large effect as compared to the mean number of forms distributed in a locality.

The large incumbent politician effect on BISP form distribution is perhaps driven by factors that reinforce each other. In the first instance, parties tend to nominate a contesting candidate from a locality, which has relatively greater political power in terms of the number of registered voters and important political figures. This helps the political party to get maximum votes from that location.[14] In turn, when a party contestant wins the elections it increases the likelihood of getting direct and indirect transfers including cash transfers from the current program.[15]

***Table 3.4***
*Regression Results for Political Determinants of BISP Forms Distribution*
*[All Forms with Own Definition of Rural/Urban]*

| Variables | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Socio-Economic Factors** | | | | |
| Population | 0.02*** | 0.02*** | 0.02*** | 0.02*** |
| | (6.12) | (4.88) | (5.99) | (5.47) |
| School | 1.05 | 0.92 | 2.8 | 2.11 |
| | (0.27) | (0.22) | (0.76) | (0.56) |
| Mud House | -0.38 | -0.66 | -0.72 | -1.01 |
| | (-0.52) | (-0.91) | (-1.16) | (-1.59) |
| Potable Water | -2.48** | -2.47** | -1.99** | -1.81* |
| | (-2.14) | (-2.11) | (-1.99) | (-1.97) |
| Electricity | 0.77 | 1.10* | 1.34** | 1.82** |
| | (1.26) | (1.74) | (2.25) | (2.80) |
| Very Urban | 304.36** | 403.46** | 231.55** | 245.32** |
| | (2.02) | (2.67) | (2.14) | (2.31) |
| Semi Urban | 50.58 | 153.59** | 86.54 | 92.7 |
| | (0.60) | (2.08) | (1.46) | (1.57) |
| Rural | -89.26** | -62.25* | -76.59** | 64.95* |
| | (-2.56) | (-1.94) | (-2.30) | (-1.89) |
| **Political Factors** | | | | |
| Turnout | 4.35 | 5.59* | 4.27* | 3.31 |
| | (1.62) | (1.86) | (1.66) | (1.26) |
| Presence of Important Politician | | | | |
| Close politician | 139.04*** | | | |
| | (2.91) | | | |
| MPA/MNA/ Senator/ Runner-up | | 68.51 | | |
| | | (0.99) | | |
| Incumbents | | | 367.20*** | 380.71*** |
| | | | (4.80) | (4.97) |
| Loyal Localities | 88.27* | 81.12* | 36.87 | |
| | (1.95) | (1.77) | (1.11) | |
| Swing Localities | 103.67** | 105.79** | 80.66* | |
| | (2.20) | (2.19) | (1.92) | |
| Absolute Winning Margins | | | | -287.93** |
| | | | | (-2.51) |
| **Constant** | -271.71* | -324.18* | -270.82* | -134.04 |
| | (-1.69) | (-1.83) | (-1.77) | (-0.82) |
| **R-squared** | 0.75 | 0.73 | 0.81 | 0.81 |
| **Number of Observations (Localities)** | **101** | **101** | **101** | **101** |

Notes: The dependent variable is the number of all forms distributed by all parliaments per locality in District Swabi. The *t*-ratios with heteroscedasticity-robust are given in parenthesis. * = significance at 10% level (two-tailed test), ** = significance at 5% level (two-tailed test), *** = significance at 1% level (two-tailed test).

In addition to the main regressions, we divide the BISP forms into ANP/non-ANP and local/non-local politicians and run regressions to examine variations in distribution patterns across different group of parliamentarians. ANP is the political party, which governed the province at the time of the launch of program in 2008 and had maximum elected representatives from the district. Local politicians, on the other hand, are those politicians who belong to and are elected from district Swabi. These local politicians are elected parliamentarians who distributed their quota of BISP forms among different localities within the district. Results of these four specifications are reported in table 3.5.

The table 3.5 reports results with the narrow definition of Important Politician (incumbent politician). Results based on other definitions are reported in the appendix (Appendix IV to VII). As mentioned in our descriptive analysis of the variables, 43% of total BISP forms distributed in district Swabi were by ANP parliamentarians while non-ANP parliamentarians distributed the rest. ANP was also the major political party in the ruling collation in the province where this district is located. Similarly, on the local vs non-local distinction, 80.3% of the BISP forms were distributed by parliamentarians who belong to district Swabi while the rest of the forms distributed in the district were from non-local parliamentarians.

To some extent, the results in column 1 and 2 (Appendix IV & V) are similar to those discussed before but they also highlight some differences across the two set of divides. The distribution of ANP forms is concentrated in urban centres while non-ANP parliamentarians distribute their forms relatively equally in the very urban, very rural and urban localities. For instance, ANP parliamentarians focused their BISP form distribution in the very-urban areas of the district where they distributed 197 more forms as compared to the control group of very rural localities. Non-ANP parliamentarians, on the other hand, give greater importance to very rural localities as compared to other areas. . With regard to socio-economic variables, both ANP and non-ANP parliamentarians distribute more forms in more populated localities and less forms in localities with a greater share of mud houses.

The presence of an important politician in a locality has a large and statistically significant effect on the distribution of forms for both group of parliamentarians. The effect is larger for the non-ANP parliamentarians with 210 more forms allotted to incumbent localities as compared to 157 more forms by ANP parliamentarians. Using dummies for loyal and swing localities (with disloyal localities as control), the estimates show that ANP parliamentarians' reward loyal localities while for non-ANP parliamentarians these variables are insignificant. Replacing dummy variables of swing or loyal localities with absolute winning margins in a locality (column 4 in appendix IV and V), only the presence of an incumbent politician remains significant for the ANP parliamentarians while all other political variables are insignificant. Overall, these results show that in the case of both sets of parliamentarians, incumbency is a strong determinant of form allocation. While ANP parliamentarians focus on very-urban localities, non-ANP parliamentarians do not have such a strong urban bias.

Columns 3 and 4 of table 3.5 provide estimates of the effect of various traits on forms distributed by local and non-local parliamentarians (detailed estimates are in Appendix VI and VII). Two clear differences emerge. Voter turnout and the presence of an important politician in a locality exert a positive influence on the distribution of distribution in the case of local parliamentarians. In the case of non-local parliamentarians, these two factors are not important. Consistent with Besley et al. (2004), it seems that locally elected politician oversupply their own localities at the expense of other localities. . In sharp contrast, non-local parliamentarians allocate more forms to loyal (to local politicians) or swing localities. Differences in allocation may be due to the fact that local parliamentarians are more embedded in their localities and have informational advantages in monitoring the distribution of forms as compared to non-local parliamentarians. Furthermore, it is not surprising that incumbency does not play a role in the case of non-local parliamentarians as there is no reason for them to reward voters living in localities with incumbent politicians. Instead, the greater importance of loyal and swing localities may reflect tactical allocation of resources with a view to winning future elections in such localities.

**Table 3.5**
*Regression Results for Political Determinants of BISP Forms Distribution*
*[Forms Distributed by ANP Parliamentarians]*

| Variables | ANP | Non-ANP | Local | Non-Local |
|---|---|---|---|---|
| **Socio-Economic Factors** | | | | |
| Population | 0.008*** | 0.012*** | 0.015*** | 0.005*** |
| | (5.39) | (3.36) | (4.54) | (3.26) |
| School | -1.68 | 4.48 | -1.2 | 3.99 |
| | (-0.77) | (1.25) | (-0.33) | (1.41) |
| Mud House | -0.68* | -0.03 | -0.7 | -0.02 |
| | (-1.67) | (-0.06) | (-1.10) | (-0.05) |
| Potable Water | -0.62 | -1.37* | -1.3 | -0.68 |
| | (-1.34) | (-1.76) | (-1.38) | (-1.09) |
| Electricity | 0.43 | 0.91 | 1.69*** | -0.35 |
| | (1.16) | (1.53) | (2.76) | (-0.90) |
| Very Urban | 196.55*** | 34.86 | 131.15 | 100.26 |
| | (3.53) | (0.25) | (1.28) | (0.85) |
| Urban | 40.08 | 46.48 | 56.84 | 29.72 |
| | (1.32) | (0.81) | (1.02) | (0.82) |
| Rural | 2.84 | -79.43** | -60.16* | -16.42 |
| | (0.19) | (-2.51) | (-1.91) | (-1.26) |
| **Political Factors** | | | | |
| Turnout | 0.51 | 3.76 | 6.73** | -2.46 |
| | (0.43) | (1.50) | (2.61) | (-1.19) |
| Presence of Incumbent Politicians | 157.25** | 210.02* | 314.16*** | 53.11 |
| | (2.25) | (1.81) | (4.05) | (0.70) |
| Loyal Localities | 48.41** | -11.52 | -13.86 | 50.75** |
| | (2.00) | (-0.29) | (-0.42) | (2.33) |
| Swing Localities | 27.79 | 52.89 | 14.54 | 66.14** |
| | (1.58) | (1.17) | (0.37) | (2.35) |
| **Constant** | 1.74* | -272.56* | -337.87** | 67.05 |
| | (0.02) | (-1.90) | (-2.19) | (0.65) |
| **R-squared** | 0.7 | 0.54 | 0.73 | 0.32 |
| **Number of Observations (Localities)** | **101** | **101** | **101** | **101** |

Notes: The dependent variable in the specification from 1-4 is the number of all forms distributed by ANP (1), Non-ANP (2), Local (3) and Non-Local (4) parliamentarians per locality in District Swabi. The *t*-ratios with heteroscedasticity-robust errors are given in parenthesis. * = significance at 10% level (two-tailed test), ** = significance at 5% level (two-tailed test), *** = significance at 1% level (two-tailed test). No of Observations = 101 localities

## 3.7 Concluding remarks

There is a large body of empirical literature, both for developed and developing countries, on the role of political factors in influencing the transfer of resources from federal to state/province level governments. Similarly, another strand of literature focus on the political distribution of service delivery and resources at the village/municipality levels within a district by locally elected governments. Both these strands of literature, however, ignores how federal politicians play a role in within district/state distribution of funds.

Taking advantage of the unique features of a social protection program in Pakistan, this chapter investigated the impact of political and socio-economic factors in influencing the distribution of a federal cash grant program, the Benazir Income Support Program (BISP), across localities within a district. The chapter combined three different data sets at the locality level. These included data on the distribution of BISP forms, census data and data gathered by the researcher on urbanization and socio-economic conditions of localities and the 2008 general elections results. The analysis was based on 101 localities located in Pakistan's Swabi district.

Using these data, proxies for various political factors were created which were combined with locality-specific socio-economic control variables to explain variation in forms distribution across localities within the district. The political variables included, voter turnout, presence of an important politician in a locality, and the swing/loyal nature of a locality.

The analysis, based on a range of specifications using different proxies for 'important politician' and other political variables, confirmed the substantial role played by political factors in explaining intra- district variation in the distribution of BISP forms. The most prominent variable explaining variation across localities was the presence (or absence) of an important politician in a locality. In particular, the presence of an incumbent politician residing in a locality played a substantial and statistically significant role in explaining variation across localities. Incumbent politicians favoured their own constituencies/localities and supplied them with 410 more BISP forms as compared to localities without incumbent politicians.

Other political variables such as voter turnout and whether a locality was a swing or loyal locality also played a role in determining form allocation, although the effects were not as strong as that of the presence of important politician in a locality. Swing localities, that is, where the 2008 election was closely contested, received significantly higher number of BISP forms as compared to localities that were tilted more towards one or another political party. This implies that political competition may be able to offset the effect of incumbent politicians' oversupply of resources to their own localities.

With regard to the non-political explanatory variables, there was a clear urban bias in the allocation of forms. Urban localities, as defined according to the 1998 census, received 181 to 273 more BISP forms as compared to rural localities while a four-part division of rural and urban displayed that very-urban localities received 231 to 403 more BISP forms as compared to the very rural localities. These patterns suggest that informational advantages and access to political party offices in urban locations place the urban poor in a better position as compared to poor households living in rural areas. Despite having a higher density of poverty, rural localities received relatively less attention in terms of accessing BISP forms. This is also confirmed by the weak link between various proxies of poverty (share of mud houses, access to potable water) and access to BISP forms.

While this paper focused on a specific, albeit, large and important social protection program in Pakistan, the unequal geographical distribution of resources in the country is a broader issue of concern. The country continues to rely on discretionary distribution of development funds, which are placed at the disposal of politicians at federal, provincial and local level. The current chapter suggests that at least from the perspective of poverty reduction, discretionary powers over fund distribution may need to be curtailed or subjected to additional rules. At the same time, the flow of resources on the basis of the patterns detected in this paper does not mean that the BISP forms end up in the hands of the non-deserving but it does mean that the chances of a poor household getting BISP forms does depend on location of his/her residence. While the findings of chapter 2 did show that distribution of forms by politician was largely pro-poor, there were still considerable leakages to the 'not so poor' households. The results of this chapter support the idea of putting some rules in place in order to restrict the discretionary role of politicians to ensure a more equitable distribution of social protection resources across localities.

 

## Notes

[1] Based on a review of the literature on Latin America, Sub-Saharan Africa and South Asia, Robinson (2007) concludes that the quality and equity of health and education services, in particular, have not improved with decentralization because these outcomes are clearly related to the availability of financial resources and local government capacity.

[2] Pork-barrel projects refer to those projects, which are intended to benefit a politician's constituents in return for political support, either in the form of campaign contributions or votes.

[3] 'Loyal' or 'Core' voters are those who are ideologically attached to a particular political party and unwilling to abandon it while 'swing' voters are those who are political moderates and are indifferent between alternative political parties and willing to abandon their ideological preferences in exchange for benefits.

[4] Special interest groups are collection of voters who share a common interest in pliable policies. The members of interest groups may differ in their views on the fixed programs and on other characteristics of the political candidates and of their parties but they have a strong incentive to cooperate with one another to influence the redistribution policies of the political parties (Grossman and Helpman 1996).

[5] The art of obtaining a grant. The idea that sub-national governments may have differential capacity to secure grants is expressed by the grantsmanship hypothesis (Stein 1981).

[6] The role of political patronage and political connections is also prevalent in other areas. For example, based on an analysis of bureaucratic appointments in Punjab, Ali (2018) found that they were highly centralized in the hands of the CM and his kitchen cabinet and were used by them to achieve specific outcomes including bureaucratic efficiency, electoral gains and personal enrichment or protection. Similarly, Saeed et al. (2015) investigated the impact of political connections on corporate financing decisions and found a positive and significant link between long-term concessionary debt and political connections. Khwaja and Mian (2005) investigated the link between borrowing and default and political connections. Based on a loan-level data set of more than 90,000 firms during the period 1996-2002 they found that politically connected firms borrowed 45 percent more and had a 50 percent higher default rate.

[7] A recent judgment of the Supreme Court of Pakistan prevented the prime minister and other federal ministers from allocating funds to their favoured regions – see http://www.supremecourt.gov.pk/web/user_files/File/const.p.20_2013.pdf.

[8] In every election, in some conservative parts of Pakistan, political party candidates bar women voters through a 'consensus' at the constituency level. As in other parts

of Pakistan, the same happened in Swabi in 38% of the localities during the February 2018 elections. https://www.dawn.com/news/290065 ). In 2017, the Election Commission of Pakistan (ECP) had to introduce a new law where an election was termed null and void if women voters' turnout is less than ten percent of the total votes in a constituency. https://www.ecp.gov.pk/Documents/laws2017/Election%20Act%202017.pdf.) Besides this, while women are 48.8% of the total population, they are only 44.1% of total registered voters https://www.ecp.gov.pk/frmGenericPage.aspx?PageID=3047)

[9] www.ecp.gov.pk

[10] Census in Pakistan is a controversial issue as cross-province resource distribution is mainly based on population. As per the constitution of Pakistan, a census should be held after every 10 years. The census which was pending in 2008 was conducted only in 2017 after a Supreme Court decision. Detailed census data is however still not available.

[11] The Awami National Party (ANP) is the major left-wing political party of the district and formed its government in the province after the 2008 election with coalition partners. In district Swabi, ANP won one seat in the National Assembly and lost the second one with a thin margin. Similarly, it won four out of six seats in the Provincial Assembly. During the 2008 elections, the voters in the district were mainly divided into Pro-ANP and Anti-ANP support groups.

[12] Biradaris are endogamous patrilineal networks (Mohmand and Cheema 2007).

[13] According to the Economic Survey of Pakistan, during 2013-14, urban poverty in Pakistan was 18.2% while rural poverty stood at 35.6%. Poverty at the time of the introduction of the BISP form stood at 49.7% in rural areas and 32.7% in urban areas.

[14] While the analysis reported in this chapter provides clear statistical evidence of the effect of incumbency on resource allocation there are several reports in the popular press that have also pointed this out. For example, in 2012, I wrote about the allocation of grants by the Pakistan Peoples Party (PPP) to areas of their political dominance. See http://qissa-khwani.blogspot.com/2012/11/pakistan-spending-its-way-into-social.html . Similarly, the federal government of the Pakistan Muslim League N (PML-N) did the same during the period 2013-18 (see, https://www.dawn.com/news/1391830) and in the province of Khyber Pakhtunkhwa, its chief minister distributed discretionary funds in his the locality where he or other strong incumbents from his party resided https://www.dawn.com/news/1330564

[15] Mohmand and Cheema (2007) and Mohmand (2011) reach similar conclusions. That is, targeting of provisions between households is conditional upon political geography and membership in dominant village level patron-client factions.

# 4 Comparing Poverty Score Card Targeting With Community Based Targeting

## 4.1 Introduction

There is a common trend across developing countries to use targeted anti-poverty programs to reach out to the poorest of the poor. The need for targeted anti-poverty programs arises both to expand coverage to the poorest of the poor and to increase the level of benefits under a budget constraint (Van de Walle 1998). However, there is substantial variation across programs and countries on how to target benefits to the poor (Coady et al. 2004a, Coady et al. 2004b, Devereux et al. 2017, Morley and Coady 2003, Devereux et al. 2015, Devereux et al. 2015). The ideal solution to reach the poor is perfect targeting where the benefits reach only the target group, however, this is impossible due to informational and administrative constraints (White 2017). Due to lack of verifiable data on observable income, developing countries have experimented with different targeting methods. These methods include means testing, proxy means testing, categorical targeting, geographic targeting, community-based targeting, self-targeting and multiple targeting mechanisms.[1] Amongst the most common methods used to address the problem of unobserved income while targeting the poor are, Proxy Means Testing (PMT) and Community Based Targeting (CBT).

In the case of PMT, governments collect information on assets and demographic characteristics, which are subsequently used as 'proxies' for household consumption or income (Alatas et al. 2012). A cut-off point is arbitrarily established to define the poverty line based on a Poverty Score Card (PSC), which in turn depends on the total budget of the program. This method takes into account observable characteristics of households such as the location and quality of dwelling, ownership of durable assets, demographic structure of the household and education, amongst other traits. The idea behind PMT is that as compared to income or consumption, households' assets and demographic characteristics are harder to conceal from government surveyors. The PMT is based on clearly defined objective criteria to differentiate between poor and non-poor, which limits the possibility of elite capture. While this method requires good administrative capacity and imposes a high cost of implementation, it also lacks the ability to capture transitory income shocks experienced by a household. For instance, a household may fall into poverty due to illness but this will not be picked up by a PMT approach. Attempting to estimate household income by using proxies is likely to lead to substantial errors (Kidd 2017, Kidd and Wylde 2011). According to Kidd (2017), due to these factors, a significant disadvantage of PMT method is that it generates high exclusion errors, especially when coverage of the program is low. Even before households are surveyed, a high proportion of intended beneficiaries are likely to be excluded and exclusion errors are likely to increase during program implementation.

On the other hand, in CBT anti-poverty programs, the government identifies a group of community members who decide on who in the community should benefit from a program. To address the unobservability of household income, CBT is based on the assumption that wealth is harder to hide from one's own community than from the government. Conning and Kevane (2002) define community-based targeting as a state's policy of contracting with community groups or intermediary agents to identify recipients for benefits, monitor the delivery of those benefits, and/or engage in some of the delivery process. For example, a group of village elders may determine who receives grain provided for drought relief, or special committees composed of common community members or a mix of community members and local officials may be formed to determine program eligibility (Coady et al. 2004b). Presumably, the biggest advantage of CBT is that community leaders have a clearer understanding of what constitutes poverty in a local setting as compared to government officials and consequently they should be able to identify those who are poor with greater accuracy in their own localities. Conning and Kevane (2002) argue that local definitions of poverty are more contextualized and can capture community-specific traits that centralized proxies often miss. However, they also point out that capture of program benefits by local elites and rent-seeking behaviour of local interest groups may undermine the targeting efficiency of anti-poverty programs.

The choice between PMT and CBT is framed mainly on the basis of these theoretical trade-offs as empirical evidence is mixed. According to a meta-analysis of 122 interventions from 48 countries, Coady et al. (2004b) found that 80 percent of the variability in targeting performance was due to differences within targeting methods, and only 20 percent due to differences across methods. They found no clearly preferred method for all types of programs or all country contexts. According to them, the substantial variation in targeting performance within specific program types and specific targeting methods suggests that differences in implementation are an important factor in determining the success of targeting. In a more recent review of the literature, based on 30 targeted programs across the world, Devereux et al. (2017) endorses the conclusion reached by Coady et al. (2004b) that no single targeting mechanism works best in all contexts and that implementation is the single most important determinant of targeting success.

While there is large empirical literature on individual targeting programs and their targeting efficiency, there is however, limited work on comparing the efficacy of different targeting methods in the same socio-economic setting. The reason is that most anti-poverty targeted programs use a single method in a single setting. Empirical studies can only compare the targeting outcomes of anti-poverty programs across different time-periods and space. The current chapter aims to fill this gap by examining targeting in the context of an anti-poverty program, which moved from the use of CBT in a first phase to the use of PMT in a second phase. In the initial phase, when the government did not have enough information to identify poor households, it entrusted elected parliamentarians with the task of selecting potential beneficiaries in their own constituencies. After two years, with technical assistance from the World Bank, the government launched a countrywide census to collect data and create a Poverty Score Card (PSC) and thus replaced parliamentarian based selection of poor households with a poverty cut-off score derived from a PSC census. To investigate the relative targeting performance of the two methods, we conducted a household level survey in 24 localities of district Swabi in northern Pakistan. We compare ex-post targeting outcomes of both these methods with observations and perceptions of our trained enumerators and supervisors in district Swabi.

Section 2 briefly discusses the literature on the two methods of targeted anti-poverty programs and their trade-offs. Section 3 discusses the setting of the current research by describing the data and the data collection process in district Swabi. Section 4 contains the empirical analysis while section 5 concludes.

## 4.2 Literature Review on the Comparison between PMT & CBT

The gold standard of targeting individuals/households is a verified means test that collects (nearly) complete information on a household's income or wealth and verifies the information collected against independent sources such as pay stubs, or income and property tax records, Coady et al. (2004a). However, due to lack of verifiable income records in developing countries, other individual assessment mechanisms are used of which the most common are Proxy Mean Tests (PMT) and Community Based Targeting (CBT).

Proxy Means Testing (PMT) is a popular method used to target the poor in a growing number of developing countries, particularly in conditional cash transfer programs in Latin America. It estimates household income by associating indicators or 'proxies' with household's income or consumption. In a two-stage process, first, correlates of household income are identified through regression analysis (or principal component analysis) using Living Standard Measurement Surveys (LSMSs). A set of multiple proxies (between 10 & 30) are obtained and used to estimate a household's welfare and given a corresponding weight. Subsequently, a country or region-wide census of households is carried out to obtain data on these correlates. These census correlates with respective weights provide a scoring formula to compute PMT scores for each household. Typically, on the basis of total availability of budget for the anti-poverty program, a cut-off point is established to divide the population into poor and non-poor households.

The theoretical advantages of the PMT approach are best summarized in Stoeffler et al. (2016) which are i) PMT is relatively cheap and simple to implement because it is based on data collection for a limited set of characteristics that are easy to observe and verify; ii) PMT relies on "objective" criteria which implies credibility, fairness and robustness to manipulations in targeting decisions; iii) PMT is based on indicators (usually assets) correlated with long-term well-being rather than short-term consumption, making it particularly suited for identifying chronic poverty; and iv) because indicators are usually observable assets, PMTs often generate less disincentives to increase income, consumption or work participation as compared to other targeting methods.

However, there are built-in design errors in the PMT method, which may lead to high exclusion and inclusion errors. Simple ex-ante arithmetic simulations of the PMT targeting formula suggests that inclusion and exclusion errors are usually above 20% (Stoeffler et al. 2016). When the program's target is the poorest 10 percent of the population, PMT may exclude 60% of the poor from the program and when targeted at the poorest 20%, such exclusion errors lie between 40 to 50 percent (Kidd and Wylde 2011). According to simulation results contained in BISP grant documents of the World Bank (World Bank 2009b), if the poorest 20% of the population is set as the target group, the under-coverage rate is expected to be 61% and the leakage rate is expected to be 40% while the coverage rate is 13%. This means 61% of the poor (the poorest 20% of the population) will be excluded while 40% of the beneficiaries will be non-poor (or do not belong to the poorest 20% of population). For Sri Lanka, the under-coverage rate of a PMT program was 52% and the leakage rate was 39% when the poverty cut-off point was set at 25% of the population. Similar results can be found elsewhere where the World Bank has conducted simulation studies in their technical assistance programs to report on the targeting errors of PMT based targeted programs in developing countries. The underlying reason behind these high targeting errors using PMT is that regressions rarely explain more than half of the variation in consumption across households (Coady et al. 2004b). In a critical review of literature, Kidd and Wylde (2011) assessed the PMT methodology and concluded that other targeting methods may be better at including intended beneficiaries by avoiding the pitfalls of the PMT. To them, PMT has problems which are embedded within the regression methodology, implementation bottlenecks and its social and political costs which may jeopardize its ownership. In short, the accuracy of PMT in terms of correct identification of the poor depends largely on which proxies are applied, how they are weighed, as well as how rigorously the beneficiary identification process is implemented (Devereux et al. 2017).

Evaluating PROGRESA's methodology, Skoufias et al. (2001) found that the PMT method is relatively more effective in identifying the extremely poor localities and households. However, they found that it becomes increasingly difficult for the PMT method to differentiate between the moderately poor and the non-poor once the program has covered the extreme poor. In an earlier, comparative study of 30 targeted programs in 11 Latin American countries, Grosh (1994) found that among all other targeting mechanisms, proxy means tests tend to produce the best incidence outcomes in developing countries. However, in a more recent review of literature, Devereux et al. (2017) found studies, which report large inclusion and exclusion errors in PMT programs implemented in Brazil, Ecuador, Colombia, Egypt, Mongolia and other developing countries. The reasons they cited were serious issues in implementation, incorrect identification of proxies and other barriers to entry for the poor households.

An alternative, to overcome the weaknesses associated with PMT, is the use of CBT mechanisms to target the poor. Community participation in selecting beneficiaries has the obvious theoretical advantage of drawing on local knowledge of individual circumstances and can thus lead to improved project performance and better targeting. In an interpretative review of the literature, Conning and Kevane (2002) analysed the role of community participation in targeting the poor and found out that decentralizing the delivery system promotes cost-effectiveness and improves intra-regional targeting at low program scales. They, however, cautioned that the advantages of local information by incorporating local notions of deprivation may be tempered by the possibility of program capture by the local elite and that local preferences may not necessarily be pro-poor. Due to elite capture in high-poverty regions, inter-regional targeting may deteriorate as central grants to high poverty regions shrink (Bardhan and Mookherjee 2005). Yusuf (2010) examined the performance of 30 community-targeted programs in developing countries and found that community-targeting interventions have tremendous potential to benefit the poor as only 4 out of 30 programs were regressive in terms of benefit distribution. However, the author also observed that informational advantage is a double-edged sword for CBT programs, since due to their informational advantages, communities tend to diverge from the criteria stipulated by the central program office. Nevertheless, using implementation theory framework, Rai (2002) found out that community information can improve targeting of transfers to the poor while simultaneously reducing targeting costs. Rai (2002) propose that audits to deter the rich from participating in programs should be conducted through the recipients, as it is costly for the government and aid agencies. By providing information on each other, the author argues, recipients can improve targeting with minimum targeting cost. According to the author, if the government has no information on whether one community/locality is poorer than another then both should receive the same total transfer. However, an implication of this is that the poor villagers in the poorer community will receive a lower transfer than the poor villagers in the richer community.

The empirical evidence on CBT programs is mixed at best. Alatas et al. (2012) conduct a field experiment in 640 Indonesian villages of a cash transfer program that sought to distribute 30,000 Rupiah (about $3) to households that fell below location-specific poverty lines. They found that community based targeting performs worse in identifying the poor as compared to proxy-means test if poverty is defined in terms of PPP$2 per day threshold. However, if the community itself defines poverty and deprivation through community based methods, the results show higher satisfaction with beneficiary lists and the targeting process. They did not found evidence of elite capture in the community based targeted anti-poverty program in Indonesia. Employing village level survey data, Khan and Kurosaki (2015) evaluated the targeting performance of an intervention by a women-led and women-focused NGO in northern Pakistan where they concluded that the NGO had been able to target not only the poor villages but also the more vulnerable households. Mansuri and Rao (2004) found that projects which rely on community participation have not been particularly effective at targeting the poor. To them these projects are only helpful in creating effective community infrastructure but not a single study establishes a causal relationship between any outcome and the participatory element of a CBT project. They found evidence that CBT programs need to be context specific with well-designed monitoring and evaluation systems in place. In a randomized experiment in 500 villages in Afghanistan, aid distribution to the poorest improved in those villages where it was managed by locally elected councils as compared to those villages where it was managed by non-elected customary local leaders (Beath et al. 2013). In another study, based on randomized trials in Ethiopia, Ghana, Honduras, India, Pakistan, and Peru, Banerjee et al. (2015) found that identifying the poorest of the poor via a participatory wealth ranking process substantially increased benefits to the very poor. Alderman (2002) analysed a CBT program in Albania and found that the program was very well targeted to the poor. His findings suggest that poverty targeting through local communities is far better than that which may be expected on the basis of proxy indicators of targeting alone. The reason given in the study is the use of local information by the local community which otherwise is unlikely to be obtained through a questionnaire or formula. In another caveat, they found out that richer or unequal communities better target benefits to the poor as compared to poor communities. The reason is that households can be easily distinguished between poor and non-poor in the more unequal communities. Ravallion (2009) also found that in an anti-poverty program run by local municipalities in China, the poor in poor cities typically fared the worst in terms of funds reaching to them. This happens despite the fact that the centre provides some degree of differential cost-sharing which favors poorer municipalities. However, the author found that this does not undermine the overall poverty impact of the program while other factors like incomplete coverage appear to matter more.

A few studies that have carried out comparative analyses of the targeting efficiency of PMT and CBT programs provide mixed findings. When poverty is defined using per-capita expenditure, community based targeting performs worse in identifying the poor than proxy-mean tests particularly at the threshold level (Holmes and Jones 2010, Alatas et al. 2012). These studies, however, do not attribute the poorer performance of CBT based targeted programs to elite capture but to the use of a different definition of poverty as understood by the community. Instead, they found that community based methods result in higher satisfaction with beneficiary lists and the targeting process itself. Assessing ex-post performance of PMT and CBT programs in Cameroon, Stoeffler et al. (2016) found that CBT performs poorly in terms of selecting households with low per capita consumption as compared to PMT. Their results show that CBT attaches more value to physical and human capital as opposed to PMT, which give more weight to actual current consumption levels. However, they found that targeting errors remain high under PMT when selecting 35% of the population for program participation. In their final recommendations, the authors propose integration of PMT and CBT to improve the targeting efficiency of the programs. Examining the effectiveness of these two methods, Karlan and Thuysbaert (2013) found that both these methods performed equally in targeting the ultra-poor in Honduras and Peru. Applying various metrics to check the targeting efficiency, the authors suggest that costs should be the driving consideration in choosing methods.

This review of the literature shows that the choice of method to target the poor in a developing country depends largely on the context and administration of the program and is thus, an open empirical question. The current paper contributes to the emerging comparative literature on targeted anti-poverty programs by examining the ex-post targeting efficiency of PMT and CBT in the same settings. Systematic differences between the two methods in terms of inclusion and exclusion errors will be identified and analyzed.

## 4.3 The Setting

The Benazir Income Support Program (BISP) was launched in July 2008 with the immediate objectives of consumption smoothing and cushioning the negative effects of food crisis and inflation on the poor, particularly women, through the provision of cash transfers. Initially, a sum of Rs 1,000 per month was given to the female member of an eligible household. The monthly instalments were enhanced to Rs. 1,200 per month from 1st July, 2013, to Rs. 1,500 per month from 1st July, 2014 and further to Rs. 1,567 from 1st July, 2015. Currently, the monthly instalment to a beneficiary family is Rs. 1,611. The amount of the transfer is equal to approximately 20 % of monthly income of an average daily wager if he/she found work for the whole month and is equivalent to 10% of the government announced minimum wage for unskilled labour, though this guideline is seldom implemented. BISP is the largest ever social safety net program in Pakistan and its coverage has increased from 1.76 million beneficiaries in 2008-09 to 5.4 million in 2016-17 and is expected to reach 7.7 million by the end of the fiscal year 2017-18. Similarly, the total amount transferred to beneficiaries increased from Rs. 15.81 billion in 2008-09 to Rs. 115 billion in 2016-17.[2]

The existing growth and consolidation of the BISP is characterized by two major phases of transition. In the initial phase of BISP (2008-09 to 2010-11), beneficiaries were identified by elected parliamentarians (and their political machines) and cash transfers were delivered to eligible families by postmen of Pakistan Postal Services. In 2010-11 a major transition occurred and poor households were identified through a Poverty Score Card (PSC) based on a census of household demographics, assets, and other measurable characteristics. In the 2nd phase of the program, around 97% of beneficiary households have been receiving payments through smart card ATMs issued by commercial banks.[3]

At the start of the program in July 2008, no reliable data was available to identify the underprivileged and vulnerable households in the country. The task of identification of the potential beneficiaries of BISP was, therefore, entrusted to the parliamentarians during Phase-I of the program. Application forms were distributed among the parliamentarians in equal number (8,000 forms to each member of the National Assembly and the Senate and 1,000 forms to each member of the four Provincial Assemblies), irrespective of party affiliation. The forms received were verified through the National Database and Registration Authority's (NADRA) database and out of 4.2 million received forms 2.2 million families were found eligible for cash transfers. This phase of BISP targeting through politicians can be called as community based identification of beneficiaries.

In the second phase of the project, the Government of Pakistan decided to move from politicians' targeting to Poverty Score Card (PSC) targeting. With technical assistance from the World Bank in 2010-11, the BISP project office carried out a countrywide poverty census to collect information on various characteristics of the households and their assets and created a Poverty Score Card (PSC). The PSC based on PMT (Proxy Means Testing) was developed using the Pakistan Social and Living Standard Measurement (PSLM) 2005-06 Survey and was later updated by using PSLM 2007-08. The PMT is based on 23 variables and uses poverty characteristics that include, among other variables, household size, type of housing and toilet facilities, educational status of child, household assets, agricultural landholding, and livestock ownership (See Annexure II for all the indictors). The Nationwide Poverty Scorecard census enabled the BISP project office to identify eligible households through an application of the Proxy Means Test (PMT) that determines the welfare status of the household on a scale between 0-100. This was an effort to identify poor households through a multi-dimensional measure. The census was started in October 2010 and was completed across Pakistan except in two regions of Federally Administered Tribal Areas (FATA) where the security situation was volatile. Around 27 million households were reached through this census. About 7.7 million households were identified as living below the cut-off score of 16.17. Out of 7.7 million households, 5.6 million households were reached through cash transfers as of June 2016.[4]

In the case of the BISP, the World Bank team in collaboration with the BISP office examined 99 different models before settling on a Final Means Testing Formula (FMTF) (World Bank 2009b). The final formula included 23 variables, which were identified through regression analysis based on the PSLM data set. All the coefficients were statistically significant at the 5 percent level and the R-Square of the model was more than 55 percent. According to World Bank simulations, targeting performance rate (coverage, under coverage & leakage) improves as the target group shifts from the poorest 10% percent to the poorest 30%. Currently the BISP program administration claims to have reached 5.6 million households as on end-June 2016 from among the 27 million households surveyed, which roughly covers 19.6% of the total households.

A website[5] has been created for the program where individual application and benefit payment status can be tracked online. In phase-1 of the project, parliamentarians were given unique usernames and passwords to track the status of applicants in their constituencies. They could also check the original scanned application forms. BISP has an online grievance redressal system. However, households targeted through the program have little or no access to the internet, thus, people submit their grievances through their parliamentarians. As we noticed during fieldwork, people in remote areas of district Swabi usually came to city centres to visit internet cafes and track their cash payments. The internet cafes usually charge Rs. 20 to tell applicants about their eligibility, funds transmitted in their names and information on their money order number.

Before describing the data and presenting results of the paper, the following anecdote from our fieldwork presents an interesting case of how sensitive the program methods are to inclusion and exclusion errors.

> "Gohar Ali (age 40) & Liaqat Ali (age 42) are two brothers living in a small house in Swabi Khas, district Swabi. They both are married with two children and their kids go to a government primary school located at one kilometer distance. While Gohar Ali completed his 10th Grade, Liaqat Ali left school early in Grade 5. They do not have any landholding except their small house inherited from their father. They both are daily wagers and work depends on availability. In the first phase of BISP, when politicians were distributing the forms, they both got

> BISP forms. Gohar Ali got two forms of which only one was considered for further action. This means that another possible poor household was deprived of receiving a BISP form. Gohar Ali got an extra form due to his connections with local political elite. When both forms reached BISP office, they applied NADRA ineligibility criteria to both the households. Gohar Ali once made a Passport so that he might go to work in the Middle East (ME). However, he could not get a chance to go to ME due to lack of required money to buy a work visa to ME for himself. This, however, went against Gohar Ali's family and his household was considered ineligible. On the other hand, his brother Liaqat Ali's household was considered eligible and started receiving the BISP benefits via the Pakistan Post Office. After two years, government switched to the 2nd phase of the program where they conducted a census across Pakistan and calculated the Poverty Score Card. The old beneficiaries lists were discontinued and the new ones were introduced. Under this new targeting approach, Gohar Ali's household received the BISP cash as their PMT score was below the cut-off score of 16.17 while Liaqat Ali's household became ineligible as their PMT was above the cut-off score. Liaqat Ali lost his twin children to a disease whose treatment he could not afford. As the PSC formula favours those families who have school-going kids, Gohar Ali's family became beneficiary while Liaqat Ali's family was dropped out from the previously selected lists targeted through politicians. Both our enumerators and supervisors surveyed the household just after the PSC census and reported that both are very poor and deserve to be included in the BISP program.

Our enumerators and supervisors observed several stories like the one above in different localities of the district. Gazdar and Zuberi (2014) also documented such stories in their fieldwork in the provinces of Punjab, Sindh and AJK region. The authors observed that small errors in reporting on the part of either respondent or the enumerator can translate into large differences with regard to eligibility as per the PSC formulae. Gazdar and Zuberi (2014) also found that there were localities which were not surveyed and were thus poor households were excluded. They also observed that census teams of the BISP did not follow a door-to-door method. Often, surveys were conducted at central locations where representatives of each household gathered to get their forms filled thus increasing the chances of misreporting. Their findings also revealed that, almost exclusively, respondents were male adults and there was no direct interaction between survey teams and women.

## 4.4 Data

The objective of the current chapter is to compare the ex-post performance of CBT and PMT methods in targeting poor households in a district when the program design phased out from CBT to PMT. For this purpose, we designed the data collection in such a way that the same households were tracked through different stages of inclusion/exclusion into the program.

Initially, we purposively selected 24 localities (1/4$^{th}$ of total 101 localities) from district Swabi. These localities were chosen to cover the geography, ethnicity, electoral constituency and rural/urban makeup of the district. In the next step, from these 24 localities, we randomly choose a sample of 3,151 households (about 8% of the BISP form recipients) from a list of households which had received BISP forms from local parliamentarians as they considered them poor and eligible for BISP grants. This sample of 3,151 households contained both recipients and non-recipients of BISP benefits as not all BISP form recipients were grant recipients. In the next stage, we attempted to trace each of the 3,151 households and obtained their poverty scores based on the data set collected by the government as part of its attempt to use PMT as the basis for targeting. We were able to obtain information on poverty scores for 2,363 of the 3,151 households. We, then, trained some 48 female enumerators (group of 2 enumerators per locality) to collect data on the poverty status of households. The enumerators collected data on household characteristics using the same questionnaire that was used by the BISP office for poverty scorecard calculations. In addition to these questionnaires, the enumerators also ranked each surveyed household in six different categories of poverty status. This ranking was based both on the responses to the questionnaire and the perception of enumerators of overall household conditions during their visit. Lastly, we collected data on these sampled households through trained supervisors who carried out focus group discussion with key informants in each locality and compiled data on poverty status of sampled households. Both the enumerators and supervisors ranked the surveyed households as per the collected information through questionnaire and their own perception and observation of poverty according to the socio-economic conditions in each locality.

The rest of this section will describe the data in detail and will comment on the data collection process to understand the analysis in later sections.

### 4.4.1 Baseline Data on Politicians' Targeting

As has been mentioned in the previous chapters, initially, for a quick launch of the program, parliamentarians were asked to identify beneficiary families. All parliamentarians, irrespective of their party affiliation, were provided with an equal opportunity to recommend eligible families. Each parliamentarian was supposed to distribute the received forms among the poor and the needy in their constituency guided by a 13-point criteria developed by the federal government.[6]

We treat this initial distribution of BISP forms by political leaders in district Swabi as baseline data. The form distribution exercise took place in 2008, when members of the four Provincial Assemblies, the National Assembly and the Senate distributed these BISP forms all over Pakistan among the 'deserving and needy' by themselves or through their 'political machines'. We compiled a complete list of all households that received BISP forms from the politicians in district Swabi. A total of 40,254 forms were distributed in 101 localities. Of these, 60% of the form recipients were deemed eligible after NADRA restrictions were applied. About 20% of the form recipients were deemed ineligible while the rest of the forms were withheld for further verification. In the first stage of data collection for this chapter, we selected 24 localities out of a total of 101 localities. These localities were purposively selected to represent the diverse geography, ethnicity, social and political landscape and rural/urban makeup of the district[7]. Having selected these localities, we randomly selected a sample of 3,151 households from the set of BISP form recipients.

Practically, the initial phase of the BISP program was a hybrid one with features of formulae based grant program at the district level and locally administered decentralized non-formulae based program. This means that each district received a fixed number of forms proportional to its population as represented by national and provincial assemblies' constituencies. However, there is no formula (or restrictions on parliamentarians) for forms distribution within the same constituency. To reach the poor during the first phase of the program, there were three tiers of verification of the poverty status of the BISP applicants. In the first phase, a political party member of the National or Provincial Assembly distributed the forms through party offices, political activists or in an individual capacity. Political parties have an organizational setup at the level of District, Sub-district and Union Councils (municipality). UC is the lowest level in the administration of each district, which on average contains 2-3 localities. There are no specific criteria about how many forms should be distributed within each UC or locality. Using their local knowledge, political activists distributed the BISP forms in their locality.

The second tier of selection into the program depends on the verification of the details of the applicants by the members of the local UC. Once the BISP form reaches the household, it has to be filled-in by the household with applicant information regarding family income and other detailed information. Before handing over the form to a member of the Parliament through political activists at the local level, the form has to be signed and verified by any member of the UC. At the time of verifications of these forms in 2008, each UC had a local body consisting of 13 members who had been elected through non-party elections. At this layer of verification of the applicant's eligibility, it is unlikely that a member of the UC will decline to verify an applicant's eligibility even if the applicant belongs to a rich household. Yet the process has a degree of self-selection as there is social stigma attached to receiving a meagre amount (BISP transfer) for a rich household.

Theoretically, targeting through local politicians has the obvious benefits of using local information to identify the poor in their localities. These local politicians are well-embedded in society and a fair distribution of these forms among the deserved is likely to translate into political benefits. On the other hand, political costs for the parliamentarians maybe high if the forms go to the non-poor. Chances of distributing these forms amongst their own party workers is high but there are also chances that these forms will be distributed among people who belong to other parties. During our own survey, we found out that some families were given more than one form by politicians belonging to different political parties. While at the end of the day only one form is going to be accepted, this limits the coverage of the program to reach more people. At the outset, the design of the program in this first stage limited elite capture as a number of checks were place. However, the problem of exclusion could be very high as the most marginalized people have little political connections but at the same time 'buying' their loyalty with BISP forms can pay off in the next elections.

### 4.4.2 Eligibility based on NADRA Criteria

When completed forms received by the BISP head office and verified both by members of the UC and of the Parliament and duly signed by the recipients and parliamentarians, are delivered to the NADRA head office, they are subjected to further scrutiny. NADRA has a management information system (MIS) where any citizen who is registered with NADRA has a Computerized National Identity Card (CNIC). NADRA has the following information regarding each registered citizen and which they can verify; i) government or semi-government servant or pensioner ii) holder of Machine Readable Passport (MRP) iii) holder of a bank account in any foreign bank iv) holder of National Identity Card for Overseas Pakistanis (NICOP) & v) number of members in a family which is traced through a unique family number.

A final list of eligible, ineligible and withheld applicants was prepared by NADRA in the form of a database and handed over to the Management Team of the BISP. Application forms were rejected based on an ineligibility criteria prescribed for the program. Withheld forms are those where there are discrepancies in the application form or forms that are not accompanied by relevant documents. In the case of our sample of 3,151 form-recipient households, around 2,326 households (75% of total) were deemed eligible while 808 (25% of total) households were deemed ineligible. Most of the households (80%) deemed ineligible fell in this category due to the presence of a passport holder in the household. In 808 ineligible households in NADRA criteria, 687 households were ineligible because of having a passport, 106 due to being in government service while the rest due to other reasons.

The ineligibility criteria limits the political distribution of forms which may both be good or bad for the targeting of the program. While being a government servant or having a bank account in a foreign bank can be a good check on limiting the selection of rich households into the program, the passport condition may also exclude the poor from the program. A recent UNDP report on multi-dimensional poverty in Pakistan estimated that 43.8% of the population in district Swabi was poor in 2014-15 with the intensity of poverty as high as 48% (UNDP 2016a). To escape this poverty, a household's male adult members often look for work abroad, especially in the Gulf countries. A passport is the basic requirement to access such work opportunities. During the survey, we found that most of the passport holders had never visited the Gulf.

### 4.4.3 Data on Poverty Scorecard Targeting

Soon after its start-up phase, the BISP adopted a Poverty Scorecard (PSC) based approach for beneficiary identification. Initially, a poverty scorecard census was piloted in 16 districts in 2009, and then rolled out nationwide, in phases, from 2010 to 2012. BISP chose to outsource the data collection process to a number of organizations (which it called Partner Organizations or POs), including the Population Census Organization (PCO), which is responsible for conducting the national housing and population census; consulting firms; and a nationwide NGO network of rural support programs, the Rural Support Programs Network (RSPN). The BISP census was supported by a Public Information Campaign (PIC) which was carried out in two phases. The first phase involved a national media campaign run by the BISP office itself, outlining the salient features of the program on radio, television and in the print media, and informing the recipient audience that a census was going to be held. The other form of the PIC was a forward campaign run by the POs in a particular area, with the objective of informing area residents of the impending census.[8]

Of the 3,151 households who had received BISP forms, we were able to track 2,363 households who had also been surveyed by the Poverty Score Card survey teams. On the BISP website, every household can find its poverty score based on the PSC formula by entering a Computerized National Identity Card (CNIC) number. The PSC questionnaire contains six sections. These sections gather information on geographical location, information about the household head, a detailed household roster, household composition, education attainment, number of rooms in the house, movable assets and ownership of agricultural land.[9] The important sections that determine the poverty score of each household are contained in section D (See appendix II) where 13 questions are designed to calculate the poverty score of each household. The poverty score card used in the census emphasizes asset enumeration (of land, livestock, means of transport, and household goods), and also includes information on social indicators of the household such as information on the extent of education of the household head, the number of dependents in the household, number of school going children, type of sanitation system, and the number of rooms in dwellings, among other assets.

For this chapter, we harvested data from the BISP website. From the website it was possible to obtain information on the poverty score associated with households. Households with a PSC of 16.17 or less were classified as poor and were treated as eligible for BISP benefits. It should be noted that the government did not construct district or region specific poverty scores thus the cut-off is not sensitive to variations in poverty across regions and districts. At a later stage, the program accepted appeals from households that fell within a narrow band above the cut-off score (up to 20.0) and/or if these households also had extraneous circumstances such as disability, widowhood or chronic illness.

In 2011, BISP hired a consulting firm to conduct a Targeting Process Evaluation (TPE)[10] of the BISP program. The firm submitted its report in May 2013. The report covered the four components of TPE: (i) The Targeting Process (ii) Data Entry (iii) Grievance Complaints (iv) Payments complaints. The TPE's main focus was to assess whether BISP or its POs implemented the targeting process following the methodology described in the targeting manual. The TPE observed the targeting process through the shadowing of 3,290 household interviews across the country and their main findings are discussed below.

According to the TPE, the BISP penetration in the 2nd phase was commendable due mainly to engagement of community leaders. However, it also observed that there were challenges and difficulties, which led to considerable variance from the prescribed process. The field staff was not equipped adequately, they did not make use of maps and GPS systems and while the census method aimed to visit every household, this objective was not achieved (GHK Consulting Limited 2013). The TPE also observed that enumerators generally did not enter residences but instead gathered at a Hujra or mosque (a combined community place) or at the end of street and as a result did not observe the household's assets and conditions. The TPE observed that enumerators filled poverty scorecards at a central place in a street against the guidelines of going to the doorstep. The partner organizations offered meagre payments to the enumerators for the survey due to which the motivation level of the enumerators was low. In addition, households with no male members at the time of surveys were penalized as there were no women enumerators to interact with female household members. There were cases across Pakistan where enumerators were not paid in time, which resulted in demotivation of the field staff. The TPE analysis indicates that there was significant variance between their findings on household size and the information collected by concerned POs. There were also issues of lack of proper training of the enumerators where the TPE found out that numerous answers to the questions in the survey were wrongly put in the Poverty Score Card Survey. For example, enumerators were not quite clear about the type of toilets in the household and mixed things up while noting it down in the questionnaire. In other cases, enumerators did not ask questions regarding household's assets. The TPE also found out that enumerators were not supervised, there were no field monitors and due to the meagre payments, enumerator turnover was high.

In Peshawar, it was observed that in some UCs the households were called to a specific place through a focal person and their forms collectively filled. In its final recommendations, TPE advised the government to use categorical criteria to minimize inclusion and exclusion errors. For example it recommended that households with borderline poverty scores but extraneous characteristics such as illness, disability or non-availability of a bread winner can appeal for inclusion. It also recommended the use of a parallel verification exercises using community-based wealth and poverty rankings. They advocated statistical audits of beneficiary households to verify information provided to PSC enumerators. A mechanism for grievances was also in place to rectify the errors during PSC survey but the marginalized poor would have been least able to pursue their grievance complaints, as the process was cumbersome and costly in terms of travel. In addition, no district specific poverty score cards thus failing to capture the variance across districts. Same poverty scorecard was used for Rural and Urban localities which have completely different poverty dynamics.

Besides, there were many articles, reports and opinion pieces in Pakistan's press about mismanagement of the poverty census and that many localities/regions were not included in the census.[11] There are now reports that BISP project office is in the middle of revising the PSC formula with several additional features to improve its performance.[12] These features include improved welfare indicators, excluding non-verifiable indicators, and including location and interaction effects. To capture geographical location as an important determinant of poverty, the new PSC formula is planning to incorporate interactions between urban status and agro-climate zones to improve the prediction of the model.

### 4.4.4 Data on Enumerator's Perception of Poverty of Surveyed Households

To assess and compare the targeting outcomes of the PMT and CBT methods, we utilize the concept of multidimensionality of poverty as consumption or income alone may not be able to capture poverty. For this purpose, we trained 48 female enumerators from 24 localities. These enumerators conducted a survey of those households who had received BISP forms from politicians. Groups, formed of two female enumerators, were given the task of surveying both eligible and non-eligible households. A majority (42 out of 48) of the female enumerators were residents of the localities which they surveyed. They were given a questionnaire which had to be filled within the premises of the house being surveyed. The enumerators were asked to seek responses from recipient (women) of the BISP form. The questionnaire was constructed in such a manner that it captures the poverty scorecard variables and some extra information. The emphasis was to go inside the house to observe and record the data as per the questionnaire. As discussed earlier, the official Poverty Score Card survey was meant to be a door-to-door census but it was observed that this was not always the case and often questionnaires were filled by enumerators at a central location (Farooq 2014, Naqvi et al. 2014, Mumtaz and Whiteford 2017, Jalal 2017, GHK Consulting Limited 2013, Gazdar and Zuberi 2014).

When the trained female enumerators visited households to fill in the questionnaire, they also observed the condition of the house, the living standard of household members and other movable and immovable assets. After filling the questionnaire, the enumerators carried out a poverty ranking exercise. Based on their observation of the housing conditions, the daily routine of members of the households and their subjective judgment on the importance of each of these traits, they placed the surveyed households into one of six poverty categories. The female enumerators are mostly from poor or lower middle-income classes and work as day-labourers' in various survey exercises conducted by the government or civil society organizations. Prior to the survey, they were provided a 3-day training and were asked to define poverty in the local context and then were told to rank each household in different ranks of poverty. An outline (see Appendix VIII) was constructed in consultation with all enumerators to rank households in six different ranks before the start of survey.

Compared to the official PSC teams, these female enumerators are more embedded in the local settings and are likely to have background information about the families they visited. On average, these enumerators visited 10 households each day and were paid Rs. 20 per questionnaire as against Rs. 5 given to PSC surveyors. Only one group of enumerators dropped out from the survey in the middle of it due to illness at home while the rest completed their work. The enumerators retrieved data on 1,692 households, which is 54% of our baseline data set of 3,151 households.

### 4.4.5 Data on Supervisors' Perception of Poverty of Surveyed Households

To cope with enumerator bias, we employed another layer of supervisors to report on the poverty conditions of households in the framework of multidimensionality of poverty. We employed 6 male supervisors to report on household (multidimensional) poverty by ranking different households into the six different categories defined earlier by the female enumerators.

These supervisors visited each of the 24 localities one at a time and conducted focus group discussions with community elders, religious leaders, local councillors and politicians and specifically reached out to the Kasab Gar/Dams.13 These supervisors worked with the forms that had been filled-in by the enumerators and verified the poverty status of each household during these focus group discussions. At first, the various community actors sat together to develop a list of characteristics that differentiated poor households from the wealthy ones in their community. Subsequently, they determined the poverty status of each household. Data on ranking of 2,523 households on poverty (80% of total of base line data set) was retrieved by these supervisors. The supervisors were able to track more households than the enumerators because they did not visit a particular household for verification but worked with the community to rank households.

Table 4.1 provides information on the various sources of data collected for this chapter and a categorization in terms of eligible/poor or ineligible/non-poor status. To reiterate, information was first collected on a sample of 3,151 BISP-form recipient households located in 24 localities. Subsequently, the NADRA ineligibility criteria were applied and a total of 2,326 households started receiving the transfer while 808 households were deemed ineligible for the transfer. Of these 3,151 BISP-form recipients, we traced 2,363 who were included in the Poverty Score Card (PSC) survey in 2011. Of those who were included in the PSC survey, based on the poverty cut-point of 16.17, only 846 households were deemed eligible for the cash transfer. Finally, in order to compare the effectiveness of the CBT and the PMT methods, we trained a set of enumerators and supervisors to collect data on poverty status. Of the total 3,151 households, our enumerators were able to track 1,692 households. Of these 1,692, - 1,377 households were classified as poor by the enumerators. The supervisors could track 2,523 households and placed 2,066 households in the poor category.

***Table 4.1***
*Data Type by Source*

| Data Type by source | Surveyed | | Not surveyed | Total | Total Surveyed localities | Total Localities in District |
|---|---|---|---|---|---|---|
| | Poor | Non-Poor | | | | |
| **Politicians' forms distribution (Base Line Data)** | 3,151 | 0 | 0 | 3,151 | 24 | 101 |
| **Poverty as per NADRA's eligibility criteria** | 2,326 | 808 | 17 | 3,151 | 24 | 101 |
| **Poverty per Poverty Score Card if cut off point is 16.17** | 846 | 1,517 | 788 | 3,151 | 24 | 101 |
| **Poverty per perception of Enumerators** | 1,377 | 315 | 1,459 | 3,151 | 24 | 101 |
| **Poverty per perception of Supervisors** | 2,066 | 457 | 628 | 3,151 | 24 | 101 |

## 4.5 Research Methodology[14]

Before reporting the results, I briefly present the different indicators used for measuring the targeting efficiency of CBT and PMT methods. The section also presents the statistical methods used to identify determinants (households' characteristics of) experiencing exclusion and inclusion errors under the two methods.

***Table 4.2***
*Targeting Matrix*

| **Poverty Status** | **Beneficiary Status** | | **Total** |
|---|---|---|---|
| | Beneficiary | Non-Beneficiary | |
| Poor | Correct Inclusion (C1) | Incorrect Exclusion (E2) | **P** |
| Non-Poor | Incorrect Inclusion (E1) | Correct Exclusion (C2) | **NP** |
| **Total** | **B** | **NB** | **Total** |

In terms of the efficiency of the targeting mechanism, there are two types of mistakes which are faced by any program intervention. The first is that of failing to reach the target population described as an F-mistake, i.e. a failure in the prime objective of the intervention. The second type of mistake is made when the intervention reaches the non-target population. This is termed as an E mistake as it implies excessive coverage (Cornia and Stewart 1993).

Both these indicators will be used to establish targeting efficiency. In this chapter they are termed as inclusion (E1) and exclusion error (E2) as shown in Table 4.2. Inclusion error (or Leakage) is the incorrect inclusion of non-poor as beneficiary of program benefits while exclusion error (or under-coverage) is the incorrect exclusion of poor from the program benefits. An Inclusion Error (IE) index measures the share of non-poor beneficiaries over the total number of beneficiaries while an Exclusion Error (EE) index measures the share of poor non-beneficiaries over the total number of poor. We will then compare targeting efficiency by comparing these two indices across different targeting methods.

An exclusion error index measures the share of poor non-beneficiaries (E2) over the total number of poor (P): $EE{=}E2/P$ (Table 4.2). Similarly, an inclusion error index measures the share of non-poor beneficiaries (E1) over the total number of beneficiaries (B): $IE{=}E1/B$. It is then possible to compare targeting efficiency for a given method $j$ ($IEj$ and $EEj$) with an alternative method $k$ ($IEk$ and $EEk$) (Stoeffler et al. 2016).

Besides estimating targeting errors, the chapter also explores the determinants of these targeting errors.

## 4.6 Results on Targeting Performance

This section presents results in two parts. In first part, contained in section 4.6.1 to 4.6.3, inclusion and exclusion errors based on three different targeting methods are reported and analysed. In 4.6.1, inclusion error in politicians' forms distribution are calculated as per perception of poverty of enumerator and supervisors. In section 4.6.2, both inclusion and exclusion errors, as perceived by enumerators and supervisors are reported when NADRA's criteria is being applied on politicians' distribution of forms. Similarly, in section 4.6.3, inclusion and exclusion errors as perceived by enumerators and supervisors are reported for the PSC targeting method. In the second part of our results, contained in section 4.6.4, determinants of targeting errors are calculated and reported.

### 4.6.1 Inclusion Errors in Politicians' Forms Distributions

We begin by evaluating the targeting performance of politicians' distribution of BISP forms in district Swabi from the perspective of the trained enumerators and supervisors. Out of 3,151 households, the enumerators surveyed 1,692 households while the supervisors surveyed 2,523 households. The left part of Table 4.3 provides statistics on the inclusion error[15] calculated on the basis of enumerator perception of household poverty during their visits to the households. At the end of every questionnaire, which took 20 minutes on average, enumerators ranked households on their poverty status into six different categories from very poor to very rich (see Appendix VIII for the ranking).

The left part of Table 4.3 shows the distribution of households in these six different poverty ranks as per observations and perception of the enumerators. As shown in panel B of the table, 81.4% of the households who received forms from the politicians were ranked as very poor, poor or near poor while the rest (18.6%) were termed as non-poor, the mistargeted. Most of the households are in the category of poor while only 7% are either rich or very rich. The difference between the very poor and the poor is limited - while the 'very poor' have no source of income, the 'poor' have only one income earner and that too a daily wage earner below the minimum wage level.

The right part of Table 4.3 shows the distribution of households in six different poverty ranks as per supervisor rankings. As shown in panel B of the table, 81.89% of the households in the parliamentarian beneficiary lists fall in the overall poor category while less than 18.1% fall in the non-poor category. Panel A of the table shows that only 5 percent of the total beneficiaries were rated as rich or very rich.

***Table 4.3***
*Inclusion Errors in Politicians' targeting as per Enumerators & Supervisors*

| Panel (A) | | | | | | |
|---|---|---|---|---|---|---|
| | Enumerators' Perception | | | Supervisors' Perception | | |
| **Poverty Status** | **No of households** | **Percent** | **Cum.** | **No of Households** | **Percent** | **Cum.** |
| 1. Very Poor | 233 | 13.77 | 13.77 | 797 | 31.59 | 31.59 |
| 2. Poor | 1,091 | 64.48 | 78.25 | 1,097 | 43.48 | 75.07 |
| 3. Near Poor | 53 | 3.13 | 81.38 | 172 | 6.82 | 81.89 |
| 4. Average | 193 | 11.41 | 92.79 | 337 | 13.36 | 95.25 |
| 5. Rich | 116 | 6.86 | 99.65 | 95 | 3.77 | 99.02 |
| 6. Very Rich | 6 | 0.35 | 100 | 25 | 0.99 | 100 |
| **Total** | **1,692** | **100** | | **2,523** | **100** | |

| Panel (B) | | | | |
|---|---|---|---|---|
| | Enumerators' Perception | | Supervisors' Perception | |
| **Poverty Status** | **No of households** | **Percent** | **No of Households** | **Percent** |
| Poor (1+2+3) | 1,377 | 81.38 | 2,066 | 81.89 |
| Non-Poor (4+5+6) | 315 | 18.62 | 457 | 18.11 |
| **Total** | **1,692** | **100** | **2,523** | **100** |

Before combining the enumerators and supervisors' observations to evaluate the targeting accuracy of politicians' distribution of BISP forms, Appendix IV provides a picture of the similarities and differences in the observations of the survey households that were surveyed by both enumerators and supervisors. Both the supervisors and enumerators perceptions about the poverty status of visited households are well-matched (Appendix IX). Overall, both groups identify 87.4% of households as either poor or non-poor and only 12.6% of the households were evaluated differently. Given the similarity, and in order to highlight the comparison between politician versus enumerator and supervisor targeting, enumerator and supervisor observations are combined to check the targeting efficiency of politicians' distribution for a larger number of households (see Table 4.4).

***Table 4.4***
*Inclusion Errors in Politicians' Targeting as per Enumerators & Supervisors Combined*

| Poverty Ranking | Total Observations | Percent | Cum. |
|---|---|---|---|
| **Poor** | **2,287** | **78.62** | **78.62** |
| Poor to One/Non-Poor to Other | 164 | 5.64 | 84.26 |
| Non-Poor | 458 | 15.74 | 100 |
| **Total** | **2,909** | **100** | |

Out of 3,151 households, 2,909 households were surveyed by either enumerators or supervisors or by both. According to their observations, 78.6 percent of households were correctly targeted by politicians, 15.74 percent were incorrectly targeted and should not have been included in the program. The remainder (5.64 percent) of the households were either poor or non-poor defending on the observation of supervisors or enumerators.

### 4.6.2 Inclusion and Exclusion Errors in NADRA's Ineligibility Criteria

Out of 3,151 households, we have information on 3,134 households after application of NADRA's ineligibility criteria. Out of these 3,134 households, our trained enumerators reached out to 1,691 households and our supervisors reached 2,512 households. The results shown in Table 4.5 reflect enumerator and supervisor assessment of these households who were either poor or non-poor according to NADRA's ineligibility criteria.

After applying NADRA's ineligibility criteria, a total of 358 households were deemed ineligible of the 1,691 households surveyed by the trained enumerators (left part of Table 4.5). According to the enumerators, of these 358 households, 36% (130 out of 358) were correctly excluded. However, according to the enumerators, the application of NADRA' ineligibility criteria also led to the exclusion of 228 of 358 (64%) poor households from the program beneficiary lists. With the application of the NADRA, inclusion error is reduced to 13.8% (184 out of 1333) as opposed to 18.6% (314 out of 1691) in the case of politicians' beneficiary lists. However, 16.6% (228 out of 1377) of the poor (identified correctly by the politicians) were excluded from the beneficiary lists after application of NADRA ineligibility criteria. As per the enumerators' perception, the overall targeting error (summation of incorrectly identifying the poor and non-poor) worsens after application of the NADRA's ineligibility criteria. Overall, according to the enumerators, politicians correctly identified 81.4% (1377 out of 1691) of the households to be included in the program while the imposition of NADRA's ineligibility criteria leads to correct identification of 75.6% ((1149+130)/1691) to be either included as they were poor or be excluded as they were non-poor. The analysis of the numbers shows that NADRA's centralized ineligibility criteria works towards reducing inclusion errors but in doing so it increases exclusion errors – in other words, it excludes a smaller proportion of rich households while at the same time excluding a larger proportion of poor households. Most of the exclusion occurs as a number of poor households may have an individual with a passport and this makes them ineligible based on NADRA's criteria.

The results shown in the right part of Table 4.5 provides inclusion and exclusion errors after the imposition of NADRA's ineligibility criteria as per our supervisors' observation. Out of 3,151 households, 2,518 households were observed by supervisors. Of these, 1,882 were deemed eligible while 636 were ineligible as per NADRA's criteria.

***Table 4.5***
*Inclusion & Exclusion Errors in NADRA's Targeting as per Supervisors*

| Panel (A) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Enumerators' Observation | | | | Supervisors' Observation | | | |
| Poverty Status | Beneficiary On NADRA | | Non-Beneficiary on NADRA | | Beneficiaries On NADRA | | Non-Beneficiar-ies on NADRA | |
| | Obs | percent | Obs | percent | Obs | percent | Obs | percent |
| Very Poor | 198 | 14.85 | 35 | 9.78 | 661 | 35.12 | 136 | 21.38 |
| Poor | 916 | 68.72 | 175 | 48.88 | 852 | 45.27 | 240 | 37.74 |
| Near Poor | 35 | 2.63 | 18 | 5.03 | 107 | 5.69 | 65 | 10.22 |
| Average | 122 | 9.15 | 70 | 19.55 | 197 | 10.47 | 140 | 22.01 |
| Rich | 59 | 4.43 | 57 | 15.92 | 50 | 2.66 | 45 | 7.08 |
| Very Rich | 3 | 0.23 | 3 | 0.84 | 15 | 0.8 | 10 | 1.57 |
| **Total** | **1333** | **100.01** | **358** | **100** | **1882** | **100.01** | **636** | **100** |
| **Panel (B)** | | | | | | | | |
| | Enumerators' Observation | | | | Supervisors' Observation | | | |
| Poor | 1149 | 86.2 | 228 | 63.69 | 1620 | 86.08 | 441 | 69.34 |
| Non-Poor | 184 | 13.8 | 130 | 36.31 | 262 | 13.92 | 195 | 30.66 |
| **Total** | **1333** | **100** | **358** | **100** | **1882** | **100** | **636** | **100** |

With NADRA's criteria, inclusion error reduced to 13.9% (262 out 1,882 households) as compared to 18.1% (457 out of 2,518 households) based on politicians' beneficiary list. However, NADRA's restrictions applied to politicians' beneficiaries list also resulted in a very high exclusion error of 21.4% (441 poor households were excluded out of 2,061 total poor households). A large proportion of poor households identified by politicians were deemed ineligible by NADRA's centralized ineligibility criteria as per the observation of our trained supervisors. NADRA also correctly excluded 42.6% or 195 non-poor households of a total of 457 non-poor households, who had been included in the program by politicians. Overall, according to supervisors, politicians correctly identified 81.9% (2,061=1,620+441 poor households out of 2,518 total households) of the households to be included in the program while NADRA's ineligibility criteria correctly included or excluded 72% ((1,620+195)/2,518) of the households.

**Table 4.6**
*Inclusion & Exclusion Errors in NADRA's Targeting as per Enumerators & Supervisors combined*

| Enumerators' & Supervisors' Combined Data | NADRA's Eligibility | | | | |
|---|---|---|---|---|---|
| | Beneficiary | | Non-Beneficiary | | Total |
| | Observations | Percent | observations | Percent | |
| Poor | 1,796 | 83.19 | 486 | 65.32 | 2,282 |
| Poor to One/ Non-poor to other | 122 | 5.65 | 42 | 5.65 | 164 |
| Non-Poor | 241 | 11.16 | 216 | 29.03 | 457 |
| Total | 2,159 | 100 | 744 | 100 | 2,903 |

Results of inclusion and exclusion errors based on the combined data set of enumerators and supervisors is reported in Table 4.6. A total of

 

2,903 households were ranked by enumerators or supervisors. Of these households, 164 were rated differently by enumerators and supervisors. Of the remainder (2,739 households), based on NADRA's ineligibility criteria, the inclusion error is reduced to 8.8% (241 non-poor out of 2,739 households) as compared to 16.68% (457 non-poor out of 2,739 households) in the case of politicians' beneficiary lists. However, the exclusion errors due to NADRA's ineligibility criteria is quite high as 17.7% (486 poor households were excluded out of 2,739 households) of poor households were excluded from the program. While politicians correctly identified 83.3% (2,282 out of 2,739) of households to be poor, after the imposition of NADRA's ineligibility criteria 73.45% (1,796+216 out of 2,739) were correctly identified. This reinforces the earlier finding that while the imposition of NADRA's ineligibility criteria reduces inclusion errors, it does so at the costs of increasing exclusion errors.

### 4.6.3 Inclusion and Exclusion Errors in PMT Targeting.

This section calculates inclusion and exclusion errors based on comparing the poverty scorecard approach and the poverty rankings provided by enumerators and supervisors. These findings are also compared with inclusion and exclusion errors based on politicians targeting and targeting performance after the imposition of the NADRA criteria. Of a total of 3,151 politicians' selected households, we were able to track 2,363 households and obtain their poverty scores, and of these 2,363, our enumerators were able to track and rank 1,311 households into poor and non-poor while our supervisors were able to track and rank 1,909 households. We then combined both enumerator and supervisor observations which yielded data on 2,189 households.

 

***Table 4.7***
*Inclusion & Exclusion Errors in PMT's Targeting*

| Poverty Status | Beneficiaries per PMT | | Non-Beneficiaries per PMT | | Total |
|---|---|---|---|---|---|
| | Observations | Percent | Observations | Percent | |
| | **Panel A-Enumerators versus PMT Targeting** | | | | |
| Poor | 370 | 87% | 707 | 80% | 1077 |
| Non-Poor | 54 | 13% | 180 | 20% | 234 |
| Total | 424 | 100% | 887 | 100% | 1311 |
| | **Panel B-Supervisors versus PMT Targeting** | | | | |
| Poor | 607 | 88% | 981 | 80% | 1588 |
| Non-Poor | 82 | 12% | 239 | 20% | 321 |
| Total | 689 | 100% | 1220 | 100% | 1909 |
| | **Panel C-Enumerators & Supervisors versus PMT Targeting** | | | | |
| Poor | 657 | 85% | 1090 | 77% | 1747 |
| Poor/Non-Poor | 45 | 6% | 84 | 6% | 129 |
| Non-Poor | 75 | 10% | 238 | 17% | 313 |
| Total | 777 | 100% | 1412 | 100% | 2189 |

Of the 1,311 households and after the application of the cut-off score of 16.17, the PSC method placed 424 households in the beneficiary category and the remainder in the non-beneficiary pool (Panel A in Table 4.7). As per the observations and rankings of enumerators, the inclusion error based on the PMT method is 13% (54 out of 424 households) while the exclusion error is very high at 66% (707/1077). In comparison, the inclusion error in this sample of 1,311 households in the case of politicians' targeting was 17.8% (234 out of 1,311 households). The PMT method also excluded 66% of the households that were considered poor based on politicians' targeting.

Panel B in Table 4.7 presents inclusion and exclusion errors based on the PMT method as per the perception and observations of the supervisors. While the inclusion error is low at 12% (82 out of 689 households), the exclusion error is very high with 62 % (981 out of 1,588) of the poor households (according to supervisors) being excluded from program access based on the Poverty Score Card (PSC) formulae. As compared to politician targeting, more than half (981 out of 1909) of the households are excluded from the beneficiary list. On the other hand, 75% (239 out of 321 households) of the non-poor were rightly excluded by the PSC formulae, however, these households constitute only 12.5% (239 out of 1909) of the total households reached by politicians.

In Panel C of Table 4.7, we combined both the enumerator & supervisor data and evaluated the targeting efficiency of PSC method by calculating the inclusion and exclusion errors for a larger sample. Data on 2,189 households who were reached either by our enumerators or supervisors or by both. Of these 2,189 households, 777 households are below the PSC cut-off point of 16.17 and are thus beneficiaries while 1,412 households are above the cut-off point and were thus excluded from the program benefits in the second phase of the BISP program. We exclude 129 observations from our analysis as both the supervisors and enumerators did not agree on their poverty status.

The inclusion error, according to enumerators and supervisors, after the application of the PSC formula is 10% (75 non-poor out of 777 total beneficiary households). However, exclusion error is 62% (1,090 poor out of total poor households of 1,747) after the application of PSC formulae. Based on the observations of enumerators and supervisors, the PSC approach is successful in removing a large proportion of the non-poor from the program but it excludes an even larger share of households from the program who were earlier identified as poor in CBT method by politicians. As discussed earlier, this high targeting error in the PMT method maybe due to the built-in design flaws in the PSC method such as low explanatory power of its regression methodology, incorrect identification of poverty proxies and implementation bottlenecks.

### 4.6.4 Determinants of poverty status

This section examines and compares differences in means of socio-economic characteristics of households who were classified as poor or non-poor based on different targeting methods. Table 4.8 examines differences in household socio-economic characteristics across poor & non-poor households based on the perception and observation of enumerators and supervisors. Given the similarity in the enumerators and supervisors ranking of households on the basis of poverty, as discussed in the previous sections, it is expected that households classified as poor by enumerators and supervisors will have similar socio-economic characteristics. Based on the first set of variables pooled under 'household composition', the results shows that both enumerators and supervisors are more likely to place a household in the non-poor category if a woman recipient is educated, household head is educated, and, on average, if the educational endowment of a household is higher. Both enumerators and supervisors give importance to the variables that capture the feminization of poverty. They are both more likely to place households in the category of poor if a household is headed by a woman, a BISP recipient is a widow, single woman households or households with women as only adult members. Similarly, households belonging to the lower caste are more likely to be ranked as poor by both enumerators and supervisors.

On the employment indicators, enumerators and supervisors are more likely to rank households as non-poor if the household has any member in government service, is a government pensioner, runs a business, a household member is abroad, or a Dehkan (farmer). Presence of a daily wage earner leads to a greater likelihood of being placed in the poor category according to both enumerators and supervisors. Overall, according to both enumerators and supervisors the presence of any working person in the household increases the chances that a household is placed in a non-poor category. For example, according to enumerators the share of households where at least one person works is 75.6 percent amongst the non–poor and 57% among the poor.

In terms of housing characteristics as well, there is a high degree of consistency between enumerators and supervisors. Households placed in the poor category have similar housing conditions regardless of enumerator or supervisor rating. The same picture holds with regard to household durable assets and lack of land holdings.

In the last column of table 4.8, we formally test differences in means of the households ranked poor by enumerators and supervisors. To underline, the previous discussion, in 8 out of 15 indicators of household composition, there are no statistically significant differences in means of the traits. In other variables in the household composition category, there are differences but the differences are small in magnitude. In 6 out of 9 indicators on employment characteristics of households, there are no statistically significant differences between enumerators and supervisors. On all indicators of household assets, there are no significant differences.

***Table 4.8***
*Mean Comparison of Determinants of Poverty as per Enumerators' and Supervisors' Perception*

| | Enumerators Perception (Means) | | | Supervisors Perception (Means) | | | Enumerator's vs Supervisor's poor |
|---|---|---|---|---|---|---|---|
| **Household Characteristics** | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | Poor | Non-Poor | t-test [Diff of Means] (1)- (2) | Poor | Non-Poor | t-test [Diff of Means] (4)- (5) | t-test [Diff of Means] (1)- (4) |
| **Household Composition** | | | | | | | |
| Age of BISP recipient (in Years) | 47.663 | 46.536 | 1.127 | 47.213 | 45.595 | 1.619** | 0.449 |
| BISP recipient educated | 0.1 | 0.146 | -0.046** | 0.093 | 0.206 | -0.113*** | 0.007 |
| Female headed household | 0.359 | 0.219 | 0.140*** | 0.336 | 0.179 | 0.156*** | 0.023* |
| Household head educated | 0.142 | 0.225 | -0.083*** | 0.144 | 0.294 | -0.152*** | -0.002 |
| Household average education | 2.005 | 3.112 | -1.107*** | 2.107 | 3.798 | -1.691*** | -0.102 |
| BISP recipient is a widow | 0.202 | 0.108 | 0.094*** | 0.204 | 0.103 | -0.101*** | -0.002 |
| Household Size | 5.531 | 6.683 | -1.152*** | 5.895 | 7.063 | -1.168*** | -0.364*** |
| Single women households | 0.073 | 0.035 | 0.038*** | 0.049 | 0.015 | 0.035*** | 0.024*** |
| Number of dependents in household | 2.757 | 2.886 | -0.128 | 2.933 | 2.996 | -0.063 | -0.176** |
| Only woman adults in household | 0.139 | 0.067 | 0.073*** | 0.124 | 0.035 | 0.089*** | 0.015 |
| School age children | 0.617 | 0.632 | -0.015 | 0.657 | 0.687 | -0.029 | -0.04** |
| School going children | 0.462 | 0.473 | -0.011 | 0.514 | 0.567 | -0.053** | -0.052*** |
| Household belongs to the lower caste | 0.5 | 0.336 | 0.165*** | 0.465 | 0.286 | 0.179*** | 0.035** |
| Household has at least one disable person | 0.166 | 0.171 | -0.006 | 0.187 | 0.142 | 0.045*** | -0.021 |
| Household has at least one serious ill person | 0.171 | 0.19 | 0.02 | 0.162 | 0.147 | -0.015 | 0.009 |
| **Employment Indicators** | | | | | | | |
| At least 1 Govt employee in Household | 0.052 | 0.223 | -0.171*** | 0.048 | 0.223 | -0.175*** | 0.004 |
| At least 1 Semi-Govt employee in Household | 0.003 | 0.006 | -0.004 | 0.005 | 0.007 | -0.002 | -0.002 |
| At least 1 pensioner in Household | 0.007 | 0.023 | -0.015** | 0.013 | 0.039 | -0.029*** | -0.006 |
| At least 1 private employee in Household | 0.01 | 0.009 | 0.001 | 0.019 | 0.039 | -0.02** | -0.009** |
| At least 1 is doing own business in Household | 0.133 | 0.209 | -0.08*** | 0.131 | 0.208 | -0.077*** | 0.002 |
| At least 1 is abroad in Household | 0.018 | 0.127 | -0.109*** | 0.023 | 0.153 | -0.13*** | -0.005 |
| At least 1 is daily wager in Household | 0.346 | 0.289 | 0.057** | 0.414 | 0.344 | 0.071*** | -0.068*** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| At least 1 is Dehkan in Household | 0.073 | 0.111 | -0.038** | 0.081 | 0.099 | -0.017 | -0.008 |
| At least 1 is working in Household | 0.571 | 0.756 | -0.185*** | 0.646 | 0.842 | -0.197*** | -0.075*** |
| **House Condition** | | | | | | | |
| Having own house | 0.821 | 0.949 | -0.128*** | 0.781 | 0.943 | -0.162*** | 0.039*** |
| Rooms in House | 1.67 | 2.36 | -0.688*** | 1.67 | 2.39 | -0.715*** | 0 |
| Rooms per person in House | 0.397 | 0.433 | -0.036* | 0.375 | 0.392 | -0.017 | 0.022** |
| Rooms per adult in House | 0.6 | 0.622 | -0.022 | 0.578 | 0.612 | -0.034* | 0.022 |
| Roof is concrete | 0.236 | 0.508 | -0.273*** | 0.279 | 0.647 | -0.368*** | -0.043*** |
| Has flush toilet | 0.216 | 0.553 | -0.337*** | 0.198 | 0.642 | -0.445*** | 0.018 |
| Pumped drinking water | 0.091 | 0.267 | -0.176*** | 0.102 | 0.347 | -0.245*** | -0.011 |
| Gas as fuel | 0.021 | 0.037 | -0.015* | 0.051 | 0.159 | -0.108*** | -0.03*** |
| Has electricity | 0.951 | 0.987 | -0.0357*** | 0.95 | 0.998 | -0.048*** | 0.001 |
| Electricity bill | 559 | 527 | 31.4 | 294 | 521 | -227*** | 265* |
| **Durable Assets** | | | | | | | |
| Has fridge | 0.173 | 0.606 | -0.434*** | 0.159 | 0.985 | -0.826*** | 0.014 |
| Has Freezer | 0.007 | 0.013 | -0.006 | 0.004 | 0.026 | -0.022*** | 0.003 |
| Has Microwave | 0 | 0.003 | -0.003 | 0 | 0.002 | -0.002 | 0 |
| Has Washing Machine | 0.086 | 0.235 | -0.149*** | 0.079 | 0.326 | -0.247*** | 0.007 |
| Has Air cooler | 0.005 | 0.029 | -0.024*** | 0.007 | 0.046 | -0.039*** | -0.002 |
| Has Air conditioner | 0 | 0 | 0 | 0 | 0.002 | -0.002 | 0 |
| Has TV | 0.166 | 0.365 | -0.2*** | 0.163 | 0.455 | -0.292*** | 0.003 |
| Has a Truck | 0.001 | 0.013 | -0.012** | 0 | 0.011 | -0.011** | 0.001 |
| Has a Car | 0.002 | 0.048 | -0.045*** | 0.002 | 0.035 | -0.033*** | 0 |
| Has Motorcycle | 0.015 | 0.146 | -0.131*** | 0.018 | 0.118 | -0.100*** | -0.003 |
| Has Animals | 0.285 | 0.343 | -0.058** | 0.299 | 0.398 | -0.099*** | -0.014 |
| **Land Holdings** | | | | | | | |
| Have some land (Survey) | 0.14 | 0.373 | -0.233*** | 0.111 | 0.425 | -0.314*** | 0.029** |
| Have more than 0.5 Acre of Land (Survey) | 0.058 | 0.268 | -0.21*** | 0.049 | 0.294 | -0.245*** | 0.009 |

P values significance *=0.10 **=0.05 ***=0.01; No of maximum observations for Enumerators = 1,692 ;No of maximum observations for Supervisors = 2,523

Table 4.9 presents differences in means between those households identified as poor by politicians and households identified as poor using the poverty scorecard method. Of the five education related variables, the Poverty Score Card method values education or its lack more than politicians. If a household has children of school going age or school going children, PSC method would more likely to include them into poor as compared to the baseline targeting by politicians. However, the poverty Score Card method does not seem to give as much importance to the feminization of poverty as compared to politicians. Households which are headed by females, having a widowed recipient, single women households or only women adult households are more likely to be included in the category of poor households by politicians as compared to the PSC method. Similarly, the presence of a seriously ill person is visible to the politician as compared to the PSC method. This was also recognized by program officials and in BISP redressal cases, households with seriously ill persons were included in the program provided their PSC score was between 16.17 and 20 points.

On the employment indicators, PSC has mixed effects on the targeting outcome. If a household has a person working in the government sector, then the PSC method is more likely to exclude the household from the program as compared to politicians. However, politicians are more likely to include a household in the program if the household has no working person.

On the condition and facilities at the house, PSC method is more likely to notice the absence of these facilities as compared to the politicians. Similarly, household durable assets and landholdings of the households are more likely to be counted via PSC method as compared to the politicians' targeting.

***Table 4.9***
*Mean Comparison of Determinants of Poverty as per Politicians & PSC*

| **Household Characteristics** | **Politi-cians** | **PSC** | | **Differences of Mean** | |
|---|---|---|---|---|---|
| | Poor | Poor | Non-Poor | Politicians Poor vs PSC Poor | PSC Poor vs PSC Non-Poor |
| **Household composition** | | | | | |
| Age of BISP recipient (in Years) | 47.454 | 44.821 | 47.827 | 2.633*** | -3.006*** |
| BISP recipient educated | 0.109 | 0.068 | 0.124 | 0.041** | -0.056*** |
| Female headed household | 0.333 | 0.297 | 0.333 | 0.036 | -0.036 |
| Household head educated | 0.158 | 0.108 | 0.193 | 0.05** | -0.085*** |
| Household average education | 2.211 | 1.847 | 2.423 | 0.364*** | -0.576*** |
| BISP recipient is a widow | 0.184 | 0.149 | 0.189 | 0.035* | -0.04* |
| Household Size | 5.745 | 6.83 | 5.331 | -1.085*** | 1.499*** |
| Single women households | 0.066 | 0.047 | 0.067 | 0.019 | -0.02 |
| Number of dependents in household | 2.781 | 3.896 | 2.379 | -1.115*** | 1.517*** |
| Only woman adults in household | 0.126 | 0.094 | 0.129 | 0.032* | -0.035* |
| School age children | 0.619 | 0.811 | 0.57 | -0.192*** | 0.241*** |
| School going children | 0.464 | 0.641 | 0.422 | -0.177*** | 0.219*** |
| HH belongs to the lower caste | 0.469 | 0.579 | 0.414 | -0.11*** | 0.165*** |
| HH has at least one disabled person | 0.167 | 0.163 | 0.157 | 0.004 | 0.006 |
| HH has at least one serious ill person | 0.174 | 0.132 | 0.187 | 0.042** | -0.055** |
| **Employment Indicators** | | | | | |
| At least 1 govt employee in HH | 0.083 | 0.047 | 0.104 | 0.036** | -0.057*** |
| At least 1 Semi-govt employee in HH | 0.004 | 0.007 | 0.003 | -0.003 | 0.004 |
| At least 1 pensioner in HH | 0.01 | 0.002 | 0.01 | 0.008 | -0.008 |
| At least 1 private employee in HH | 0.01 | 0.009 | 0.011 | 0.001 | -0.002 |
| At least 1 is doing own business in HH | 0.147 | 0.198 | 0.123 | -0.051*** | 0.075*** |
| At least 1 is abroad in HH | 0.038 | 0.024 | 0.045 | 0.014 | -0.021* |
| At least 1 is Daily Wager in HH | 0.336 | 0.375 | 0.343 | -0.039 | 0.032 |
| At least 1 is Dehkan in HH | 0.08 | 0.068 | 0.086 | 0.012 | -0.018 |
| At least 1 is working in HH | 0.605 | 0.646 | 0.608 | -0.041 | 0.038 |
| **House condition** | | | | | |
| Having own house | 0.845 | 0.774 | 0.864 | 0.071*** | -0.09*** |
| Rooms in House | 1.803 | 1.608 | 1.804 | 0.195*** | -0.196*** |
| Rooms per person in House | 0.404 | 0.286 | 0.429 | 0.118 | -0.143*** |

| | | | | | |
|---|---|---|---|---|---|
| Rooms per adult in House | 0.604 | 0.559 | 0.604 | 0.044* | -0.045* |
| Roof is concrete | 0.286 | 0.209 | 0.298 | 0.077*** | -0.089*** |
| Has flush toilet | 0.278 | 0.197 | 0.3 | 0.081*** | -0.103*** |
| Pumped drinking water | 0.123 | 0.072 | 0.134 | 0.051*** | -0.062*** |
| Gas as fuel | 0.024 | 0.005 | 0.028 | 0.019** | -0.023*** |
| Has electricity | 0.957 | 0.943 | 0.966 | 0.014 | -0.023* |
| Electricity bill | 552.531 | 299.06 | 677.46 | 253.471 | -378.4 |
| **Durable assets** | | | | | |
| Has fridge | 0.254 | 0.156 | 0.292 | 0.098*** | -0.136*** |
| Has Freezer | 0.008 | 0.012 | 0.008 | -0.004 | 0.004 |
| Has Washing Machine | 0.113 | 0.068 | 0.125 | 0.045*** | -0.057*** |
| Has Air cooler | 0.009 | 0.002 | 0.008 | 0.007 | -0.006 |
| Has Air conditioner | 0 | 0 | 0 | 0 | 0 |
| Has TV | 0.203 | 0.141 | 0.228 | 0.062*** | -0.087*** |
| Has a Truck | 0.003 | 0.002 | 0.004 | 0.001 | -0.002 |
| Has a Car | 0.011 | 0.002 | 0.012 | 0.009 | -0.01 |
| Has Motorcycle | 0.039 | 0.033 | 0.044 | 0.006 | -0.011* |
| Has Animals | 0.296 | 0.337 | 0.277 | -0.041* | 0.06** |
| **Land holdings** | | | | | |
| Have some land (Survey) | 0.184 | 0.129 | 0.211 | 0.055** | -0.082*** |
| Have more than 0.5 Acre of Land (Survey) | 0.098 | 0.05 | 0.118 | 0.048*** | -0.068*** |

P values significance *=0.10 **=0.05 ***=0.01 Maximum number of observations is 1692.

## 4.7 Concluding remarks

A number of methods have been developed to target poverty-alleviation programs. As may be expected, there is no 'best' approach amongst these multiplicity of methods and the literature suggests that irrespective of targeting methods, the efficacy of targeting also depends on program administration and context as similar targeting methods may give different results in different circumstances and contexts. During the past two decades, the two most common methods to target benefits have been the Proxy Means Testing (PMT) approach and Community Based Targeting (CBT). However, papers that have compared the targeting performance of these two methods in the same context are rare. Pakistan's BISP program provides a unique opportunity to compare the efficiency of two targeting mechanisms in one district when the program design changed from community based targeting mechanism to poverty scorecard targeting mechanism.

To compare the two approaches, we randomly choose a sample of 3,151 households (about 8% of the BISP form recipients), located in 24 localities, from a list of households that had received BISP forms from local parliamentarians. Subsequently, we traced a subset of these households and obtained their poverty scores. We then collected data on household characteristics using the same questionnaire that was used by the BISP office for poverty scorecard calculations and asked (i) survey enumerators and (ii) survey supervisors – with the help of community leaders and key informants, all of whom were aware of the local context to use the survey information and their observations to rank each surveyed household in six different poverty categories. Through this approach, the enumerators were able to gather information and rank 1,692 households while the supervisors were able to gather information on 2,523 households. We used these different sources of information to compare the targeting performance of the PMT and the CBT methods.

The results of the various comparisons showed that community targeting by local politicians leads to targeting outcomes that are similar to those by local enumerators and supervisors. This is perhaps not surprising but it is noteworthy that essentially, three different community based targeting approaches lead to broadly similar outcomes – that is, exclusion errors are lower as compared to the poverty scorecard method. In contrast, the poverty scorecard method reduces inclusion errors but this comes at the cost of high exclusion error. Based on the combined ranking of both enumerators and supervisors observations, inclusion error in the PSC method was only 10% but there was a high exclusion error of 62%. Consistent with other studies done on community-based targeting, the large differences in targeting outcomes based on these two methods highlights that the local definition of poverty is different and context specific as compared to that based on a universal poverty scorecard method. With high exclusion errors, PMT targeting may affect the satisfaction levels of the community and may thus limit the sustainability of the program and the method.

We also used results of house-to-house survey carried out by enumerators in selected localities of the district. As may be expected, the traits of households ranked poor by enumerators, supervisors and politicians tend to coincide. A comparison of traits of those ranked poor by politicians and those ranked poor according to the PMT approach showed that the key difference was that the PMT approach undervalued the feminization of poverty and was also not sensitive to serious illnesses within a family. The analysis presented in this chapter supports the idea that the two approaches – CBT and PMT are complementary and that it may be possible to improve targeting outcomes by combining both approaches.

## Notes

[1] For a recent discussion on these methods, see Devereux et al. (2017) and White (2017)

[2] http://www.bisp.gov.pk/

[3] http://www.finance.gov.pk/survey/chapters_17/15-Social_Safety_Nets.pdf

[4] Economic Survey of Pakistan, Finance Division, Government of Pakistan, 2015-16

[5] www.bisp.gov.pk

[6] See Box A in Appendix I for the 13 point criteria

[7] Of these 24 localities, half were localities with resident parliamentarians.

[8] Benazir Income Support Program, Targeting Process Evaluation (Cluster A & B) by ICF GHK (GHK Consulting Limited 2013)

[9] Seen Appendix 2 for the Poverty Score Card questionnaire.

[10] This and the next paragraph are based on Targeting Process Evaluation by GHK, 2009(GHK Consulting Limited 2013).

[11] https://www.dawn.com/news/1397227

[12]https://dailytimes.com.pk/220710/bisp-ranked-1-among-global-unconditional-cash-transfer-programmes/ A unpublished 2017, World Bank unpublished document reveals that proxies of poverty are going to be updated from the 2007-08 to 2013-14 household survey which may reduce both the inclusion and exclusion errors based on the PMT formulae.

[13] 'Dams/Kasab Gar' is a professional caste in Swabi (and in Khyber Pakhtunkhwa province) who serve the people of a locality on occasions of happiness and sorrow. Both men and women of this caste have information about the residents of a locality they serve. They are mostly poor people living on the earnings from these service provisions. These community service providers know each household, specifically their income sources, land holdings and other assets. This knowledge is acquired by serving the villages over generations. They are messengers who inform villagers about marriages, deaths, and other important occasion on behalf of a family/household. They are paid on happy occasions by family elders while they serve without any cost if there is an occasion of sorrow in the family.

[14] This section draws on the theoretical framework developed by Coady et al. (2004a), Cornia and Stewart (1993) and the methodology developed in Stoeffler et al. (2016).

[15] Here we only have inclusion errors as we only have households that were reached by politicians with BISP forms.

# 5 Concluding Remarks

This thesis evaluated the targeting performance & political capture of Pakistan's largest social safety net program, the Benazir Income Support Program (BISP). The program which was initially launched in 2008-09 by the government of Pakistan People's Party in the name of the late prime minister, Benazir Bhutto is now in its 10th year. The program has technical and financial support from international donors including The World Bank and is the main response of Pakistan's government to provide social protection to vulnerable households. Earlier Poverty Reduction Strategy Papers (PRSPs) and a National Social Protection Strategy (NSPS) provided policy backing to BISP as the need for a targeted social protection program was highlighted in those documents.

BISP adopted two different targeting methods to reach out to the poorest of the poor. In the initial phase, which lasted from 2008 to 2011, the beneficiaries of the program were selected through parliamentarians and their political machines at the local level. The rationale for this targeting method came from the fact that in 2007-08 an immediate response was needed to support the poor who were hit by the financial crisis. Since there was no official poverty data available at the household level, the use of local information in the form of elected parliamentarians was considered to be a useful way of selecting program beneficiaries. The onus of responsibility was placed on the shoulders of elected parliamentarians based on the assumption that they are embedded among and responsible to their electorate. It is, thus, similar to community based targeting with an extra layer of being political. In the second phase of the program, based on a household level survey dataset and with the help of The World Bank, a poverty scorecard formula was devised to reach out to the poor. Subsequently, a countrywide door-to-door census was carried out during 2010-11, which collected socio-economic records of some 27 million households across the country. Based on the census data and the poverty scorecard, the old method of beneficiary selection through parliamentarians was phased out and today all households are selected into the program using a poverty scorecard cut off score.

Critical reviews of the literature on ex-post counterfactual analysis of targeted anti-poverty programs reveals that no single anti-poverty targeting method dominates over other methods. These reviews advocate for more rigorous, policy-relevant evaluations of anti-poverty programs with an open mind about methodology, adapted to the problem, local setting and data collection constraints. They also argue that future efforts to draw useful lessons from evaluations need more policy-relevant data and methods than normally used in the classic assessment of mean impact on those assigned to the program. While the impact of targeted programs and targeting methods are increasingly under scrutiny, there is little work on Pakistan. The available literature on Pakistan on the BISP and other targeted programs is scant, less rigorous and inconclusive. Literature reviewed on the BISP showed that most of the work has focused on evaluating its targeting performance under the poverty scorecard method, its role in mitigating shocks to the beneficiary households, its impact on health, education and other outcomes, and its role in empowering women. While these are all very important aspects that need to be investigated, there is almost no work which has investigated the first phase of the BISP program, that is, when politicians were entrusted with targeting program benefits to the poor. An examination of the first phase of the program, when benefits were targeted through politicians may yield important insights for policy making regarding the role of political factors and politicians in grants disbursement. While it may be not seem and indeed is not scientific to distribute programs through politicians as opposed to the use of a data-based poverty score card approach, the underlying assumption that the former method is by design inferior to a poverty means targeting/poverty score card approach, remains an untested assumption. This thesis is was an attempt to fill this research gap.

For the current research, we made use of the design features of the initial phase of targeting and then the changes in BISP's targeting design when it changed from political community based targeting to poverty scorecard based targeting. These two different targeting designs of the current BISP program offered a unique opportunity to investigate targeting performance & political capture in the Pakistani context. It also offered an opportunity to compare community based targeting with poverty scorecard targeting in the same setting and to draw policy lessons. The thesis relied on both primary and secondary data to investigate three questions, which are presented in three core essays of the current thesis. The first essay analysed targeting errors in the program during its first phase of targeting when targeting was done through parliamentarians; the second essay analysed political capture, if any, in a northern district of Pakistan; while the third essay investigated the trade-offs between two main targeting methods.

In the first essay (chapter 2), we used the Pakistan Social and Living Standard Measurement (PSLM) survey data to analyse targeting errors and benefit incidence of the program across Pakistan. The PSLM survey was conducted in 2009-10 when the BISP program was in its initial phase of targeting beneficiaries through parliamentarians. Findings of the analysis showed that BISP recipient households have significantly lower per capita annual income as compared to non-recipient households. The findings further showed that most BISP beneficiary households belonged to the poorest three quintiles. Overall, 84% of program benefits accrued to the lowest three quintiles where the first, second and third income quintiles received a share of 36%, 25% and 23% respectively.

There exists a divide in average incomes across rural and urban areas of Pakistan with lower average incomes in rural areas. We found that the poorest quintile in rural areas received a significantly higher share of benefits (40 percent) as compared to the same quintile in urban areas (23 percent). These patterns suggested that political workers are more embedded in rural settings as compared to urban settings and it is easier for them to differentiate between different levels of poverty in rural areas. In other words, the informational advantages in community-based targeting mechanisms are more pronounced in rural settings as compared to urban settings. In terms of provincial heterogeneity, targeting of households in Sindh & Punjab provinces was much better than targeting in KP and Balochistan provinces. Considerable leakages were found to the richest $4^{th}$ and $5^{th}$ quintiles in the case of KP and Balochistan. The poorest quintile in the province of Sindh received 52 percent of the forms, which is the highest across provinces. This was followed by Punjab where 38 percent of the forms went to the poorest quintile. In KP and Balochistan, the population in the $2^{nd}$ and $3^{rd}$ quintile groups received higher shares then the population in the 1st quintile group. One possible reason for this is that rural areas in Sindh and Punjab are more unequal as compared to KP and Balochistan thus it is easy for political leaders to differentiate between the poor and non-poor. Research elsewhere also suggests that it is easier for community workers to differentiate between poor and non-poor in unequal societies. Policy implications from these findings points toward advantages of using community based targeting mechanisms in rural and unequal settings.

Besides income differences, we also looked at differences in other socio-economic characteristics of BISP recipients and non-recipient households. Regarding the composition of households, BISP recipient households had more female-headed households, larger family sizes, more widowed & divorced female members as compared to non-recipient households. BISP non-recipient households had significantly better indicators of employment and education as compared to those of BISP recipient households. BISP recipient households are poorer than the non-recipients on households' durable and non-durable assets. To examine the key determinants of selection into the program, we also estimated probit marginal effects of factors affecting the probability of selection into the program. We found significant negative effects of per capita income on the probability of receiving a BISP grant, which is consistent with our earlier analysis. Similarly, compared to the control group of living in the Punjab province, probability of selection into the program is significantly higher in KP and Sindh. Probit estimates also suggested that leakages to the non-poor were more pronounced in other provinces as compared to the control group in Punjab. Overall, at the time of the survey, poverty in Pakistan was pegged at about 60% of the population and the bulk of BISP benefits flowed to the three poorest quintiles. The program targeting mechanism later changed from community-based targeting towards targeting based on poverty scorecard. This change in the design of the targeting method happened abruptly without any prior study to compare and contrast different targeting outcomes under different targeting designs. The change should have been based on empirical work where a rigorous impact evaluation exercise of the existing targeting mechanism may have guided the government to design changes. However, there was an inherent belief that an alternative was needed which would be superior to political targeting. The analysis presented in this chapter showed that this assumption may be questioned.

 

The second essay (chapter 3) examined the impact of politics, among other things, on the within-district distribution of BISP forms. Treating BISP forms as 'block grants' to parliamentarians from the federal government, the chapter investigated variations in form distribution across localities within a district. Due to its design, the BISP provided a window into how political factors may influence the distribution of benefits at the local level within a district. We examined the distribution of BISP forms across localities as a function of political explanatory variables such as voter turnout, presence of an important politician, swing or loyal nature of a locality combined with other socio-economic explanatory variables such as schooling, housing and rural-urban nature of a locality. For the variable - presence of an important politician in a locality, we used three different definitions ranging from a loose and broader definition to a stricter and limited definition.

The findings, which were consistent across different specifications, suggested a substantial role for political factors in explaining BISP forms distribution across localities in district Swabi. Presence or absence of an important politician determined forms allocation across localities and the effect was stronger when important politician was defined in the stricter sense as incumbent politician. Incumbent politicians are those who have directly received the BISP forms as their quota to be distributed by them among the poor. Poor households living in an incumbent locality had a much higher chances of receiving a BISP form as against a poor household living in a non-incumbent locality. Other political variables, such as voter turnout and whether a locality is swing or loyal, also played a role in explaining variation across localities. Among the non-political variables, the urban nature of a locality entered significantly in the model and explained a substantial share of the variation in forms distribution across localities. More urban localities received greater attention from the political community. Thus, a poor household living in a rural and non-incumbent locality had lower chances of getting a BISP form as compared to another household of similar poverty conditions living in an urban and incumbent locality. Normative considerations of efficiency and equity did not play a substantial role.

Despite clear evidence that the distribution of forms was higher in localities represented by incumbent politicians and in urban areas (chapter 3), the overall allocation of BISP forms (chapter 2) was pro-poor. Nevertheless, these finding suggest that if political targeting is used there need to be checks on the discretionary powers of politicians in order to curb the prominence of strongmen and urban areas in influencing resource allocation. For instance, political targeting maybe combined with objective criteria that either include or exclude certain types of households. Furthermore, informational advantages and access to political party offices in urban locations place the urban poor in a better position as compared to poor households living in a rural area. As a result, there is greater focus on those localities with greater knowledge of the BISP. This implies that the BISP program office needs to ensure greater access to information by designing special initiatives to increase the reach of information about the program and its targeted beneficiaries in rural areas.

The third essay reported the results of an innovative survey where a comparison of the two targeting method was carried out. The survey was conducted in 24 localities of district Swabi. Program success in targeting poor households was analysed when a loose community based targeting process was replaced with poverty scorecard to identify the poor. We hired and trained female enumerators to go inside the houses to observe household characteristics as against the official poverty scorecard census, which observed households from a distance. In the first stage, we randomly choose 3,151 households who received a BISP form from parliamentarians and compiled a data set based on the information given in the BISP filled-in forms. This initial distribution of BISP forms by politicians in 2008 was taken as baseline distribution. In the second stage, the data were divided into eligible and non-eligible households based on program administrative ineligibility criteria which was taken from the BISP project office. In the third stage, we collected data of households' poverty scores based on the census conducted by BISP office during 2010-11. In the last stage, we trained enumerators and supervisors who collected two different types of data on the sampled households. In house-to-house survey, enumerators first collected data on different socio-economic characteristics of the sampled households as per a questionnaire that was similar to the official poverty scorecard survey. These enumerators then collected data on the poverty status of each households by observing the condition of the house, facilities inside the house and the general appearance of household members. Our trained supervisors, serving as key informants, then collected data on poverty status of the sampled households based on local information and discussions with other local key informants.

We tested and compared the targeting performance of PMT and CBT methods through the observations of enumerators and supervisors. The findings suggested that community based targeting by local politicians and their political machines was associated with household poverty while the poverty scorecard method largely excluded poor households as identified by politicians. The poverty scorecard method was effective in reducing inclusion error but led to high exclusion errors and thus negatively affected the overall targeting outcome of the program. In short, all three community-based approaches – local politician, local enumerators and local supervisor based, yielded similar targeting outcomes that were quite different from targeting based on the PMT/PSC approach. The analysis showed that under the CBT, certain household traits such as - whether a household was headed by a female, where education attainment was low, where a seriously ill person lives and where there was either no working adult or only a daily wage earner to support the whole household - were more likely to obtain benefits.

Several policy lessons may be drawn from the comparison of the targeting performance of BISP program under CBT and PMT targeting mechanism. First, any shift from one targeting method to another should be based on empirical work rather than on unsubstantiated assumptions... The findings in chapter 4 revealed that CBT targeting was better than PMT at including the poor. Assuming that it is more important to include as opposed to exclude poor households, there is a strong case for complimentary of PMT and CBT methods especially when PMT method is already in place. Adding a few categorical variables (such as those which capture feminization of poverty, illness) to the poverty scorecard and some variables representing local definitions of poverty may greatly enhance the targeting performance of the PMT method. Third, our findings on community-based targeting method did not find any large scale elite capture as benefits were largely targeted towards poor households under the political-CBT method. Politicians did make choices reflective of their embeddedness in the local community with a strong eye on the political cost if their targeting was not pro-poor.

Despite the finding reported in this thesis, it is unlikely that the BISP will revert to a politician based CBT approach. However, the overall better performance of local politicians over the poverty scorecard method in targeting poor households, which may be attributed to their local knowledge of poverty, suggests that in order to avoid high exclusion errors of the

PMT approach, it may be accompanied by parallel verification exercises using community-based definitions of poverty. The use of some easily observed categorical information may fruitfully be used to reduce both inclusion and exclusion errors. This may result in better targeting; as such measures will capture locality specific poverty perceptions as against a one-size-fits-all poverty scorecard targeting approach.

# Appendices

***Appendix I:*** *The Program Eligibility and Inellegibility Criteria in Phase I*

The following categories of families were eligible:

1. Possession of CNIC by female applicant/ recipient.
2. Monthly family income is less than Rs.6000/. And subject to the conditions I and II.
3. Widowed/ divorced women, without adult male members in the family.
4. Any physically or mentally retarded person(s) in the family.
5. Any family member suffering from a chronic disease.

The following families were ineligible to receive any assistance under the Program:

6. Where any of the members of the family is in employment of government/ semi-government/ authority/ department or armed forces of Pakistan.
7. Where any of the members of the family is drawing pension from government/semi government/authority/department or armed forces of Pakistan.
8. Where any of the members of the family is receiving any post-retirement benefits from any government department/ agency.
9. Where any of the members of the family owns an agriculture land more than three acres or residential house/ plot of more than eighty square yards (3 marlas).
10. Where any member of the family is receiving income support from any other source like Punjab Food Support Scheme etc.
11. Where any member of the family possesses a Machine Readable Passport.
12. Where any member of the family possesses a National Identity Card for Overseas Pakistanis (NICOP).
13. Where any member of the family has a Bank Account (except in NBP, HBL, UBL, MCB, ABL, BOP, Bolan Bank, Khyber Bank, First Women Bank, ZTBL, Khushhali Bank, and all microfinance banks).

## *Appendix II:* BISP Census Score Card 2010-11

# BENAZIR INCOME SUPPORT PROGRAM
## COVER SHEET

Please
- Use Black Ballpoint
- Use English Block Letters
- Write One Letter in One Block

Form Number

Consecutive HH number per village

Date D D M M Y Y Y Y

### A - GEOGRAPHICAL LOCATION

1. Province
2. District
3. Thesil
4. Patwar Circle
5. Union Council
6. Village Name

### B - HOUSEHOLD HEAD INFORMATION

7. Full Name of Household Head (First, Middle and Last Name)

| First name | Middle name | Last Name |
|---|---|---|
| | | |

8. Contact Address

9. Full name of father/ husband of household head (First, Middle and Last Name)

| First name | Middle name | Last Name |
|---|---|---|
| | | |

### C - HOUSEHOLD ROSTER

| | 10. Name (First, Middle and Last Name) | | | 11. Gender<br>Male 1<br>Female 2 | 12. Relationship of member with Household head | 13. Marital status | 14. Date of Birth or age (in completed years) | | | | 15. Does member have CNIC/NIC?<br>Yes CNIC 1<br>Yes NIC old 2<br>No CNIC/NIC 3 | 16. CNIC/NIC number of adult member 18+ years of age if s/he has it | 17. Employment category over the past year (only for members aged 18 and over) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | First Name | Middle Name | Last Name | | *Codes below* | *Codes below* | DD | MM | YY | Age | | | *Codes below* |
| 1 | | | | | | | | | | | | | |
| 2 | | | | | | | | | | | | | |
| 3 | | | | | | | | | | | | | |
| 4 | | | | | | | | | | | | | |
| 5 | | | | | | | | | | | | | |
| 6 | | | | | | | | | | | | | |
| 7 | | | | | | | | | | | | | |
| 8 | | | | | | | | | | | | | |
| 9 | | | | | | | | | | | | | |
| 10 | | | | | | | | | | | | | |

Codes for 12, relationship with HH head: Head=1; Husband=2; Wife=3; Child/adopted child=4; Father/mother=5; Sister/brother=6; Grandchild=7; Son/Daughter in law=8; Sister/brother in law=9; Father/mother in law=10; Uncle/Aunt 11; Grandfather/grandmother=12; Other=13.

Codes for 13, marital status: Married=1; Unmarried=2; Divorced=3; Widowed=4; Separated=5

Codes for 17 Government= 1; Semi-government=2; Private=3, Not currently employed 4

## BENAZIR INCOME SUPPORT PROGRAM

### D- HOUSEHOLD INFORMATION

**Questionnaire for the National Scorecard for Pakistan**

| | Questions | Answers (cross the boxes or fill in the boxes for questions 1 and 5) | | | |
|---|---|---|---|---|---|
| 1 | How many people usually live and eat in the household? (do not list guest, visitors, etc…) | ☐ | | | |
| 2 | How many people in the household are under the age of 18 or over the age of 65? | 0-2 ☐ | 3-4 ☐ | 5-6 ☐ | 7 or more ☐ |
| 3 | What is the highest educational level of the head of the household (completed)? | Never attended school ☐ | Less than class 1 to class 5 included ☐ | Class 6 to class 10 included ☐ | Class 11, college or beyond ☐ |
| 4 | How many children in the household between 5 and 16 years old are currently attending schoolattending school? | There are no children between 5 and 16 years old in the household ☐ | All the children between 5 and 16 years old are attending school ☐ | Only some of the children between 5 and 16 years old are attending school ☐ | None of the children between 5 and 16 years old are attending school ☐ |
| 5 | How many rooms does the household occupy, including bedrooms and livingrooms? (do not count storage rooms, bathrooms, toilets, kitchen) | ☐ | | | |
| 6 | What kind of toilet is used by the household? | Flush connected to a public sewerage, to a pit or to an open drain ☐ | Dry raised latrine or dry pit latrine ☐ | There is no toilet in the household ☐ | |
| 7 | Does the household own at least one refrigerator, freezer or washing machine? | Yes ☐ | No ☐ | | |
| 8 | Does the household own at least one air conditioner, air cooler, geyser or heater? | Yes ☐ | No ☐ | | |
| 9 | Does the household own at least one cooking stove, cooking range or microwave oven? | Yes ☐ | No ☐ | | |
| 10 | Does the household own the following engine driven vehicles...? | At least one car / tractor and at least one morcycle / scooter ☐ | At least one car / tractor but no motorcycle / scooter ☐ | No car / tractor but at least one motorcycle / scooter ☐ | Neither car / tractor NOR motorcycle / scooter ☐ |
| 11 | Does the household own at least one tv? | Yes ☐ | No ☐ | | |
| 12 | Does the household own the following livestock...? | At least one buffalo / bullock AND at least one cow / goat / sheep ☐ | At least one buffalo / bullock BUT NO cow / goat / sheep ☐ | No buffalo / bullock BUT at least one cow / goat / sheep ☐ | Neither buffalo / bullock NOR cow / goat / sheep ☐ |
| 13 | How much agricultural land does the household own? | Area ☐ | Unit of area ☐ | | |

### E- INTERNAL PROCESS CONTROL

**Enumerator Full Name (First, Middle and Last Name)**

| First | Middle | Last |
|---|---|---|
| | | |

**Supervisor Full Name (First, Middle and Last Name)**

| First | Middle | Last |
|---|---|---|
| | | |

**Enumerator NIC /CNIC**

**Supervisor NIC /CNIC**

**Date for the interview**

| | D D | M M | Y Y Y Y | Results of Interview |
|---|---|---|---|---|
| 1 | | | | ☐ |
| 2 | | | | ☐ |
| 3 | | | | ☐ |

(1) Complete

(2) Incomplete

(3) Rejected

(4) No one home

(5) Cannot find Household

### F- DECLARATION

*I he/she also declare that the above statement is true to the best of my knowledge. I am also fully aware that incase any of the above is found to be untrue I will be struck off the list of eligible persons of the Benazir Income Support Program.*

**Applicant Full Name (First, Middle and Last Name)**

| First Name | Middle Name | Last Name |
|---|---|---|
| | | |

**Applicant Thumb Impression**

| D D | M M | Y Y Y Y |
|---|---|---|
| | | |

**Applicant Signature**

***Appendix III:*** *Marginal Effects (Dependent Variable=whether household received BISP?)*

| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|
| **Household Composition & other Characteristics** | | | | | | | |
| Female Headed Household | | 0.012 | 0.01 | 0.014 | 0.015 | 0.01 | 0.011 |
| | | (1.20) | (1.07) | (1.27) | (1.44) | (1.28) | (1.34) |
| Household Size | | -0.001 | -0.001 | 0 | 0 | 0 | 0 |
| | | (0.85) | (0.58) | (0.18) | (0.34) | (0.08) | (0.05) |
| Household has a widow | | 0.039*** | 0.039*** | 0.039*** | 0.034*** | 0.030*** | 0.029*** |
| | | (3.96) | (4.04) | (4.02) | (3.98) | (4.03) | (3.97) |
| Household has a divorcee | | 0.039 | 0.042 | 0.039 | 0.036 | 0.026 | 0.025 |
| | | (1.47) | (1.55) | (1.49) | (1.52) | (1.33) | (1.32) |
| Persons per room | | 0.002 | 0.002 | 0.001 | 0.001 | 0.001 | 0.001 |
| | | (1.08) | (0.98) | (0.90) | (0.77) | (0.65) | (0.63) |
| Share of male <18 | | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| | | (2.73) | (3.21) | (3.13) | (3.54) | (3.44) | (3.54) |
| Share of male >65 | | 0.001** | 0.001** | 0.001** | 0.001** | 0.001** | 0.001** |
| | | (2.52) | (2.41) | (2.53) | (2.32) | (2.46) | (2.40) |
| Share of female <18 | | -0.000** | -0.001** | -0.001** | -0.001*** | -0.000*** | -0.000*** |
| | | (2.26) | (2.44) | (2.48) | (2.90) | (2.83) | (2.90) |
| Share of female 18<age<65 | | 0 | 0 | 0 | 0 | 0 | 0 |
| | | (0.22) | (0.28) | (0.17) | (0.13) | (0.19) | (0.16) |
| Share of female >65 | | 0 | 0 | 0 | 0 | 0 | 0 |
| | | (0.63) | (0.83) | (0.74) | (0.98) | (0.73) | (0.64) |
| **Educational Characteristics** | | | | | | | |
| Highest level of education attained in the Household (No education=reference) | | | | | | | |
| Primary | | | -0.005 | -0.005 | -0.006 | -0.005 | -0.005 |
| | | | (0.72) | (0.74) | (1.01) | (1.14) | (1.11) |
| Middle | | | 0.008 | 0.007 | 0.003 | 0.001 | 0 |
| | | | (0.81) | (0.74) | (0.34) | (0.15) | (0.09) |

| | | | | | |
|---|---|---|---|---|---|
| Secondary | -0.004 | -0.004 | -0.006 | -0.005 | -0.005 |
| | (0.67) | (0.59) | (1.05) | (1.18) | (1.16) |
| Higher Secondary | -0.012 | -0.009 | -0.01 | -0.008 | -0.008 |
| | (1.59) | (1.19) | (1.49) | (1.49) | (1.52) |
| Higher | -0.024*** | -0.020*** | -0.020*** | -0.015*** | -0.014*** |
| | (3.79) | (3.10) | (3.38) | (3.27) | (3.26) |
| Num of children going to school | 0.004* | 0.003 | 0.002 | 0.001 | 0.001 |
| | (1.83) | (1.54) | (0.89) | (0.89) | (0.94) |
| Num of children of school going age | 0 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.08) | (0.28) | (0.61) | (0.59) | (0.60) |
| Any child in Private School | -0.015** | -0.015*** | -0.013** | -0.008** | -0.008** |
| | (2.58) | (2.61) | (2.56) | (2.00) | (2.03) |
| Child works | | -0.013* | -0.014*** | -0.012*** | -0.011*** |
| | | (1.95) | (2.65) | (3.02) | (2.92) |
| **Household Employment Characteristics** | | | | | |
| Head of Household Unemployed | | -0.004 | -0.005 | -0.003 | -0.003 |
| | | (0.64) | (0.81) | (0.66) | (0.70) |
| Ratio of Emp over Un-emp in hh | | -0.001 | -0.001 | 0 | 0 |
| | | (0.37) | (0.55) | (0.16) | (0.02) |
| Woman works | | 0.014 | 0.014* | 0.009 | 0.008 |
| | | (1.64) | (1.82) | (1.59) | (1.47) |
| (i. No occupation = reference) | | | | | |
| ii. Low Occupation | | 0.008 | 0.008 | 0.006 | 0.005 |
| | | (0.73) | (0.85) | (0.82) | (0.70) |
| iii. Middle Occupation | | -0.007 | -0.005 | 0.004 | 0.003 |
| | | (0.68) | (0.51) | (0.38) | (0.32) |
| iv. High Occupation | | -0.011 | -0.01 | -0.007 | -0.007 |
| | | (0.93) | (1.05) | (0.85) | (0.93) |
| **Source of Drinking water in HH (i. motorized pumped water=reference)** | | | | | |
| ii. Piped Water | | | 0.002 | 0.002 | 0.001 |
| | | | (0.30) | (0.28) | (0.28) |

| | | | |
|---|---|---|---|
| iii. Hand Pump | -0.006 | -0.005 | -0.005 |
| | (0.89) | (0.90) | (0.89) |
| iv. Open Well | 0.009 | 0.009 | 0.009 |
| | (0.67) | (0.77) | (0.77) |
| v. Closed Well | 0.024 | 0.011 | 0.012 |
| | (1.02) | (0.66) | (0.68) |
| vi. Pond | -0.017*** | -0.017*** | -0.016*** |
| | (2.59) | (4.10) | (4.23) |
| vii. River/Canal etc | 0.078** | 0.070** | 0.070** |
| | (2.19) | (2.12) | (2.16) |
| viii. Spring | 0.038 | 0.024 | 0.023 |
| | (0.93) | (0.90) | (0.88) |
| ix. Others | -0.016* | -0.013* | -0.012** |
| | (1.90) | (1.95) | (2.04) |
| **Presence of household utilities** | | | |
| Landline Phone | -0.008 | -0.006 | -0.005 |
| | (1.12) | (1.16) | (1.02) |
| Gas | -0.001 | 0.007 | 0.007 |
| | (0.18) | (1.28) | (1.24) |
| Electricity | 0.024*** | 0.018*** | 0.017*** |
| | (5.06) | (4.25) | (4.11) |
| **Toilet facility in the Household (i. Flush connected to public sewerage=reference)** | | | |
| ii. Flush pit-connected | 0.022 | 0.016 | 0.017 |
| | (1.12) | (1.09) | (1.11) |
| iii. Flush open drain-connected | -0.001 | -0.004 | -0.004 |
| | (0.06) | (0.39) | (0.41) |
| iv. Dry raised latrine | 0.026 | 0.019 | 0.02 |
| | (0.94) | (0.88) | (0.90) |
| v. Dry pit latrine | 0.033 | 0.03 | 0.031 |
| | (1.12) | (1.21) | (1.22) |

| | | | |
|---|---|---|---|
| vi. No toilet | 0.007 | 0.006 | 0.007 |
| | (0.37) | (0.38) | (0.43) |
| **Sewerage facility in the Household (i. Underground drain sewerage system=reference)** | | | |
| ii. Covered drain sewerage | 0.043 | 0.041 | 0.039 |
| | (1.18) | (1.14) | (1.11) |
| iii. Open drain sewerage | 0.016 | 0.014 | 0.014 |
| | (1.11) | (1.21) | (1.22) |
| iv. No sewerage system | 0.018 | 0.016 | 0.015 |
| | (1.01) | (1.09) | (1.03) |
| Household Durable Assets | | | |
| Refrigerator | | -0.008* | -0.007 |
| | | (1.71) | (1.55) |
| Freezer | | 0.007 | 0.008 |
| | | (0.56) | (0.62) |
| Air-condition | | -0.021*** | -0.021*** |
| | | (4.40) | (4.43) |
| Air cooler | | 0.006 | 0.005 |
| | | (0.47) | (0.39) |
| Fan | | 0.003 | 0.003 |
| | | (0.42) | (0.44) |
| Geyser | | -0.023*** | -0.022*** |
| | | (6.18) | (6.27) |
| Washing Machine | | 0 | 0 |
| | | (0.06) | (0.02) |
| Camera | | -0.013 | -0.013 |
| | | (1.45) | (1.49) |
| Cooking stove | | -0.012** | -0.012** |
| | | (2.40) | (2.42) |
| Cooking range | | 0.034 | 0.029 |
| | | (1.47) | (1.34) |
| Heater | | 0 | 0.001 |

| | | |
|---|---|---|
| | 0.00 | (0.11) |
| Bicycle | -0.003 | -0.003 |
| | (0.76) | (0.81) |
| Car | -0.010* | -0.010* |
| | (1.77) | (1.75) |
| Motorcycle | 0.002 | 0.002 |
| | (0.29) | (0.36) |
| TV | 0.008** | 0.008** |
| | (2.12) | (2.19) |
| VCR | 0.012 | 0.012 |
| | (0.5) | (0.51) |
| Radio | 0.011* | 0.010* |
| | (1.95) | (1.90) |
| CD player | 0.01 | 0.01 |
| | (0.77) | (0.76) |
| Sewing machine | 0.006 | 0.006 |
| | (1.41) | (1.54) |
| Computer | -0.017*** | -0.015*** |
| | (3.79) | (3.69) |
| Agricultural & Other Assets | | |
| Agriculture land (in Acres) | 0 | 0 |
| | (0.42) | (0.36) |
| Non-agriculture land | -0.011** | -0.011** |
| | (2.16) | (2.27) |
| Residential building | 0.001 | 0.001 |
| | (0.21) | (0.09) |
| Commercial building | -0.011 | -0.011 |
| | (1.49) | (1.47) |
| Agriculture as a main source of income | -0.014*** | -0.013*** |
| | (3.43) | (3.38) |
| HH Savings | 0 | 0 |
| | (0.13) | (0.59) |
| HH Jewelry | 0 | 0 |

| | | |
|---|---|---|
| | (0.02) | (0.10) |
| HH loans | 0 | 0 |
| | (1.11) | (0.94) |
| **Severely hit by inflation (i. not affected by inflation=reference)** | | |
| ii. Yes Mildly | | 0.065*** |
| | | (2.60) |
| iii. Yes Moderately | | 0.050*** |
| | | (2.60) |
| iv. Yes Highly affected | | 0.057*** |
| | | (3.23) |
| v. Yes Severely Affected | | 0.071*** |
| | | (2.69) |

The sample size is 6980 households, t-statistics in parenthesis and *, **, *** indicates statistical significance at the 10%, 5% & 1% respectively.

***Appendix IV**: Regression Results for Political Determinants of BISP Forms Distribution [Forms Distributed by ANP Parliamentarians]*

| Variables | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Socio-Economic Status & Voter Turnout** | | | | |
| Population | 0.009*** | 0.007*** | 0.008*** | 0.007*** |
| | (5.14) | (3.37) | (5.39) | (4.35) |
| School | -2.42 | -2.57 | -1.68 | -1.31 |
| | (-1.00) | (-1.01) | (-0.77) | (-0.63) |
| Mud House | -0.57 | -0.57 | -0.68* | -0.65* |
| | (-1.18) | (-1.32) | (-1.67) | (-1.69) |
| Potable Water | -0.83 | -0.81* | -0.62 | -0.44 |
| | (-1.43) | (-1.47) | (-1.34) | (-1.00) |
| Electricity | 0.21 | 0.35 | 0.43 | 0.55 |
| | (0.59) | (0.93) | (1.16) | (1.45) |
| Very Urban | 236.10*** | 258.04*** | 196.55*** | 200.23*** |
| | (3.42) | (4.00) | (3.53) | (3.65) |
| Urban | 32.24 | 64.40* | 40.08 | 35.97 |
| | (0.73) | (1.64) | (1.32) | (1.19) |
| Rural | -0.59 | 7.77 | 2.84 | 4.14 |
| | (-0.03) | (0.42) | (0.19) | (0.29) |
| Turnout | 0.64 | 0.94 | 0.51 | 0.16 |
| | (0.53) | (0.73) | (0.43) | (0.13) |
| **Presence of Important Politician** | | | | |
| Close politician | 50.15* | | | |
| | (1.89) | | | |
| MPA/MNA | | 62.98 | | |
| | | (1.46) | | |
| Incumbents | | | 157.25** | 168.96** |
| | | | (2.25) | (2.31) |
| Loyal Localities | 69.89** | 67.76** | 48.41** | |
| | (2.30) | (2.30) | (2.00) | |
| Swing Localities | 37.28* | 42.22* | 27.79 | |
| | (1.73) | (1.82) | (1.58) | |
| Absolute Winning Margins | | | | 3.46 |
| | | | | (0.07) |
| Constant | -2.69 | -17.47 | 1.74* | 32.14 |
| | (-0.03) | (-0.21) | (0.02) | (0.40) |
| R-squared | 0.65 | 0.65 | 0.7 | 0.69 |
| Number of Observations (Localities) | 101 | 101 | 101 | 101 |

Notes: The dependent variable in the specification from 1-4 is the number of all forms distributed by ANP parliamentarians per locality in District Swabi. The *t*-ratios with heteroscedasticity-robust errors are given in parenthesis. * = significance at 10% level (two-tailed test), ** = significance at 5% level (two-tailed test), *** = significance at 1% level (two-tailed test). No of Observations = 101 localities

***Appendix V**:Regression Results for Political Determinants of BISP Forms Distribution [Forms Distributed by non-ANP Parliamentarians]*

| Variables | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Socio-Economic Status & Voter Turnout** | | | | |
| Population | 0.014*** | 0.013*** | 0.012*** | 0.011*** |
| | (3.93) | (3.42) | (3.36) | (3.14) |
| School | 3.47 | 3.49 | 4.48 | 3.42 |
| | (0.94) | (0.94) | (1.25) | (0.92) |
| Mud House | 0.19 | -0.09 | -0.03 | -0.36 |
| | (0.33) | (-0.15) | (-0.06) | (-0.59) |
| Potable Water | -1.65* | -1.66* | -1.37* | -1.37* |
| | (-1.95) | (-1.90) | (-1.76) | (-1.85) |
| Electricity | 0.56 | 0.74 | 0.91 | 1.27* |
| | (0.95) | (1.26) | (1.53) | (2.07) |
| Very Urban | 68.18 | 145.32 | 34.86 | 44.96 |
| | (0.44) | (0.90) | (0.25) | (0.33) |
| Urban | 18.39 | 89.22 | 46.48 | 56.74 |
| | (0.24) | (1.33) | (0.81) | (1.00) |
| Rural | -88.66*** | -70.01** | -79.43** | -69.08** |
| | (-2.87) | (-2.47) | (-2.51) | (-2.14) |
| Turnout | 3.7 | 4.65* | 3.76 | 3.15 |
| | (1.48) | (1.78) | (1.50) | (1.23) |
| **Presence of Important Politician** | | | | |
| Close politician | 88.88** | | | |
| | (2.02) | | | |
| MPA/MNA | | 5.53 | | |
| | | (0.09) | | |
| Incumbents | | | 210.02* | 211.82* |
| | | | (1.81) | -1.86 |
| Loyal Localities | 18.42 | 13.4 | -11.52 | |
| | (0.41) | (0.30) | (-0.29) | |
| Swing Localities | 66.4 | 63.6 | 52.89 | |
| | (1.45) | (1.32) | (1.17) | |
| Absolute Winning Margins | | | | -291.41** |
| | | | | (-2.58) |
| Constant | -269.04* | -306.73** | -272.56* | -166.15 |
| | (-1.88) | (-2.07) | (-1.90) | (-1.11) |
| R-squared | 0.5 | 0.49 | 0.54 | 0.55 |
| Number of Observations (Localities) | 101 | 101 | 101 | 101 |

Notes: The dependent variable in the specification from 1-4 is the number of all forms distributed by non-ANP parliamentarians. The *t*-ratios with heteroscedasticity-robust errors are given in parenthesis. * = significance at 10% level (two-tailed test), ** = significance at 5% level (two-tailed test), *** = significance at 1% level (two-tailed test), No of observations = 101 localities

***Appendix VI:*** *Regression Results for Political Determinants of BISP Forms Distribution [Forms Distributed by Local Parliamentarians]*

| Variables | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Socio-Economic Status & Voter Turnout** | | | | |
| Population | 0.02*** | 0.017*** | 0.015*** | 0.015*** |
| | (4.56) | (3.75) | (4.54) | (4.59) |
| School | -2.69 | -2.73 | -1.2 | -1.72 |
| | (-0.70) | (-0.67) | (-0.33) | (-0.49) |
| Mud House | -0.48 | -0.72 | -0.7 | -0.81 |
| | (-0.65) | (-0.97) | (-1.10) | (-1.25) |
| Potable Water | -1.73 | -1.73 | -1.3 | -1.31 |
| | (-1.55) | (-1.58) | (-1.38) | (-1.46) |
| Electricity | 1.25** | 1.46** | 1.69*** | 1.77*** |
| | (2.19) | (2.31) | (2.76) | (2.85) |
| Very Urban | 214.04 | 288.74** | 131.15 | 133.52 |
| | (1.54) | (2.18) | (1.28) | (1.28) |
| Urban | 44.7 | 117.99 | 56.84 | 60.34 |
| | (0.60) | (1.64) | (1.02) | (1.13) |
| Rural | -66.10** | -46.84 | -60.16* | -57.05* |
| | (-2.07) | (-1.50) | (-1.91) | (-1.81) |
| Turnout | 7.05** | 7.97*** | 6.73** | 6.64** |
| | (2.61) | (2.76) | (2.61) | (2.47) |
| **Presence of Important Politician** | | | | |
| Close politician | 95.83** | | | |
| | (2.41) | | | |
| MPA/MNA | | 29.47 | | |
| | | (0.45) | | |
| Incumbents | | | 314.16*** | 312.04*** |
| | | | (4.05) | (3.99) |
| Loyal Localities | 28.79 | 23.66 | -13.86 | |
| | (0.68) | (0.55) | (-0.42) | |
| Swing Localities | 33.34 | 32.87 | 14.54 | |
| | (0.72) | (0.69) | (0.37) | |
| Absolute Winning Margins | | | | -83.13 |
| | | | | (-0.80) |
| Constant | -348.60** | -387*** | -337.87** | -311.23** |
| | (-2.14) | (-2.23) | (-2.19) | (-1.92) |
| R-squared | 0.65 | 0.64 | 0.73 | 0.73 |
| No of Observations (Localities) | 101 | 101 | 101 | 101 |

Notes: The dependent variable in the specification from 1-4 is the number of all forms distributed by Local/Resident parliamentarians per locality in District Swabi. The *t*-ratios with heteroscedasticity-robust errors are given in parenthesis. * = significance at 10% level (two-tailed test), ** = significance at 5% level (two-tailed test), *** = significance at 1% level (two-tailed test). No of Observations = 101 Localities

***Appendix VII:****Regression Results for Political Determinants of BISP Forms Distribution [Forms Distributed by Non-Local Parliamentarians]*

| Variables | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| **Socio-Economic Status & Voter Turnout** | | | | |
| Population | 0.005*** | 0.004*** | 0.005*** | 0.003 |
| | (4.19) | (2.83) | (3.26) | (1.62) |
| School | 3.74 | 3.65 | 3.99 | 3.82 |
| | (1.42) | (1.40) | (1.41) | (1.17) |
| Mud House | 0.11 | 0.07 | -0.02 | -0.2 |
| | (0.29) | (0.21) | (-0.05) | (-0.53) |
| Potable Water | -0.75 | -0.74 | -0.68 | -0.5 |
| | (-1.12) | (-1.06) | (-1.09) | (-0.72) |
| Electricity | -0.48 | -0.36 | -0.35 | 0.05 |
| | (-1.00) | (-0.85) | (-0.90) | (0.15) |
| Very Urban | 90.23 | 114.62 | 100.26 | 111.66 |
| | (0.67) | (0.78) | (0.85) | (0.95) |
| Urban | 5.93 | 35.62 | 29.72 | 32.37 |
| | (0.16) | (1.26) | (0.82) | (0.87) |
| Rural | -23.15 | -15.4 | -16.42 | -7.89 |
| | (-1.47) | (-1.18) | (-1.26) | (-0.62) |
| Turnout | -2.7 | -2.38 | -2.46 | -3.33 |
| | (-1.3) | (-1.25) | (-1.19) | (-1.45) |
| **Presence of Important Politician** | | | | |
| Close politician | 43.2 | | | |
| | (1.45) | | | |
| MPA/MNA | | 39.05 | | |
| | | (1.13) | | |
| Incumbents | | | 53.11 | 68.74 |
| | | | (0.70) | (0.87) |
| Loyal Localities | 59.51** | 57.50** | 50.75** | |
| | (2.04) | (2.05) | (2.33) | |
| Swing Localities | 70.35** | 72.95** | 66.14** | |
| | (2.53) | (2.51) | (2.35) | |
| Absolute Winning Margins | | | | -204.83** |
| | | | | (-2.25) |
| Constant | 76.87 | 62.49 | 67.05 | 177.21 |
| | (0.75) | (0.65) | (0.65) | (1.45) |
| R-squared | 0.33 | 0.32 | 0.32 | 0.33 |
| No of Observations (Localities) | 101 | 101 | 101 | 101 |

Notes: The dependent variable in the specification from 1-4 are all forms distributed by non-local/Non-resident parliamentarians. The *t*-ratios with heteroscedasticity-robust errors are given in parenthesis. * = significance at 10% level (two-tailed test), ** = significance at 5% level (two-tailed test), *** = significance at 1% level (two-tailed test). No of observations = 101 localities

***Appendix VIII:*** *Enumerators' & Supervisors' Poverty Evaluation Matrix*

| **Poverty Rank** | **Enumerators' & Supervisors' Evaluation Matrix** |
|---|---|
| Very Poor | No own house, Condition of House is very poor, Very small house, No concrete roof, No income earner, Lives on Charity, No land holdings, No Assets, A Widow, No monthly incomes, in Debts, Illiteracy or Children in Government School |
| Poor | Own or Rented small house, No Concrete Roof, At maximum only 1 daily wager, Lives on Charity & Donations, No Land Holdings, No Assets, Monthly Income is less than Rs 5,000, in Debts, Illiteracy or Children in Government School |
| Near Poor | Own small to medium size house, Partly concrete partly mud house, At maximum only 2 daily wager or small shop, at times on Charity & Donations, No Land Holdings, No Assets, Monthly Income is less than Rs 8,000, Illiteracy or Children in Government School |
| Average | Own medium size house, Concrete Roof, Medium size business or Job, Small Landholdings, Some Assets, Monthly Income above minimum income, Some Assets, Children in Private School |
| Rich | Handsome House, Multiple income earners, Good business, More than 8 Acres of Agricultural Land holding, Has Every Households Asset in the PSC, Monthly Income in 2nd top quintile, Children in Private School |
| Very Rich | Handsome Big House, Every facility at House, Earnings from salaries and Huge Land Holdings, Children in Private Schools, Have Cars |

*Appendix IX: Enumerators & Supervisors Poverty Ranking Matrix*

| Enumerators' Observations | Supervisors' Observations | | |
|---|---|---|---|
| | Non-Poor | Poor | **Total** |
| Non-Poor | 150 (11.5%) | 96 (7.3%) | **246** |
| Poor | 68 (5.2%) | 992 (76.0%) | **1060** |
| **Total** | **218** | **1088** | **1306** |

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## About the Author


Muhammad Saleem was born in Swabi, Pakistan. He holds a Master of Arts degree in Economics from University of Peshawar (Pakistan) with distinction and another Master of Arts degree in Development Studies from the International Institute of Social Studies of the Erasmus University Rotterdam in the Netherlands. After completing his MA in Pakistan, he joined State Bank of Pakistan (Pakistan's central bank) as Research Officer in its Economic Policy Department. He contributed to the Annual and Quarterly reports of State Bank of Pakistan on the state of Pakistan's economy, which served as critical evaluation of government's management of the economy. He then moved from Karachi to Islamabad and joined Planning Commission of Pakistan. He worked as Research Analyst in the Commission's anti-poverty section, which mainly provided poverty estimates to the government with policy recommendations for poverty alleviation in the country. He got a scholarship from Pakistan's Higher Education Commission to pursue Master leading to PhD in Economics from the International Institute of Social Studies. For his master thesis, he evaluated the effects of Government of Punjab Girls Stipend Program on the increase in enrolment at primary and secondary levels of schooling in Punjab, Pakistan. His PhD thesis evaluated the targeting performance of Benazir Income Support Program. Importantly, the thesis looked into the phenomenon of political capture in program targeting and compared targeting performance of the program when the program shifted from community based targeting mechanism to poverty scorecard mechanism.

Besides working for government, Muhammad Saleem worked in the development sector as freelance consultant in 2014 and completed various projects on health, education, governance, budget analysis and poverty eradication sectors. He wrote various articles in leading English papers on poverty and inequality in Pakistan. He presented his research in Pakistan and abroad. He also gave lectures on various socio-economic issues of Pakistan to students at different Pakistani universities. After completing his PhD, he intends to pursue a career in economic research and teaching at universities in Pakistan.