The Impact of Social Cash Transfers on Poverty in Pakistan-A Case Study of Benazir Income Support Programme

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The Impact of Social Cash Transfers on Poverty in Pakistan-A Case Study of Benazir Income Support Programme

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Abstract

Governments around the world often make social cash transfers to their residents for varied purposes such as consumption smoothing, poverty reduction, improved take-up of education and health services, etc. In Pakistan, these transfers took a big stride with the initiation of Benazir Income Support Programme (BISP) in 2008. Social cash transfers have multiple types of impacts e.g. on health, education, reproductive behavior, voting behavior etc. This study aims to investigate the existence of a relationship between social cash transfers and poverty. Specifically, the research question is: Is there any impact of BISP receipt on poverty in Pakistan? This research question is answered with the help of utilization of Household Integrated Economic Survey (HIES) 2015-16 (Government of Pakistan, 2017) which presents information on households' consumption (used to measure poverty) as well as households' cash transfer recipient status. Official poverty estimation methodology is used for defining the poverty status of a household. The relationship between cash transfers and poverty is studied through the nearest-neighbor matching method limiting ourselves to BISP. The findings show that there is no significant relationship between BISP cash transfer and poverty when full dataset is used and a negative but economically insignificant relationship when only people from the bottom consumption quintiles are considered. Based on these findings, way-forward in terms of future research and making necessary modifications in the programme design of BISP is suggested.

Introduction

Governments around the world often make cash transfers to their residents for varied purposes such as consumption smoothing, poverty reduction, improved take-up of education and health services, etc. These transfers are often called social cash transfers or, simply, cash transfers. In Pakistan, these transfers in the form of pensions started soon after independence. However, transfers to assist the poor took a big stride with the start of Benazir Income Support Programme (BISP) in 2008. At the provincial level as well, there are many programmes providing direct cash transfers to the beneficiaries. Only in Punjab, in the financial year 2016-17, there were around 26 cash transfer programmes providing regular or one-time benefits (Government of the Punjab, 2017). However, most of these programmes were small in size as compared to BISP.

Due to the increasing coverage and size of cash transfer programmes, it is important to assess what impacts, these programmes, particularly BISP, have had.

Social cash transfers have multiple types of impacts e.g. on health, education, reproductive behavior, voting behavior, etc. The focus of the study will be narrowed to only the poverty-related impacts of the cash transfers. This study aims to investigate the existence

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of a relationship between social cash transfers and poverty. Specifically, the research question is: Is there any impact of social cash transfers on poverty in Pakistan?

There have been many studies around the world that have measured the impact of cash transfers on poverty (for example, Agostini & Brown (2011) for Chile, Maitra & Ray (2003) for South Africa, and Van den Berg & Cuong (2011) for Vietnam). For Pakistan, Durr-E-Nayab and Farooq (2014) evaluated the impact of BISP on poverty using the Pakistan Panel Household Survey, 2010. As BISP and other cash transfer programs (e.g. Khidmat Card for Persons with Disabilities by Punjab Social Protection Authority) have expanded since 2010, it is important to utilize the latest available consumption data as presented by Household Integrated Economic Survey (HIES), 2015-16. Additionally, in previous studies of the similar nature, official poverty estimation methodology has not been used. Due to its wider acceptance, this study employs the official poverty estimation methodology which will make the results more relevant for the policymakers.

The results of this study will help the policymakers to review the social cash transfer programmes and make the necessary modifications to make them more effective. The study would have policy implications regarding targeting of the social protection programmes as well as their coverage.

Social cash transfers represent only one type of the benefits provided by the government and hence only a single side of the coin. The government also provides other benefits e.g. free or subsidized services, fee waivers, in-kind transfers etc. These benefits are offset to some extent by the taxes imposed on the households. Therefore, considering only the impact of cash transfers on poverty will yield a partial view of the situation. Agostini (2011) indicates, ignoring the tax burden of the households when consumption taxes are often regressive, the impact of social cash transfers on poverty may have an upward bias. However, due to data limitations regarding tax collection, in this thesis, we will estimate only partial effect of social cash transfers.

Literature Review

A Short History of Social Cash Transfers

The welfare of the citizens has been a function of the state since the early period of civilization. The Indian emperor Ashoka, who ruled from 268 to 232 BC, introduced the policy of *Dhamma*, which included the welfare duties of the state (Thapar, 2002). Under this policy, Ashoka planted trees to provide shade to animals and humans, dug wells and built rest houses and watering places (Thapar, 2002).

Welfare in the form of in-kind transfers for the citizens of the state could be traced as back as the Roman Empire in which grains were distributed at subsidized prices to the urban population (Erdkamp, 2013). Gaius Gracchus is credited to initiate the regular distribution of cheap grain in 123 BC. Initially, there were some restrictions on the distribution, however, in 62 BC, Cato the Younger included ‘the poor and landless plebs’ in the eligible population (Plutarch, quoted in Erdkamp, 2013). Soon, in 58 BC, the price of this free ration was abolished altogether by Clodius (Erdkamp, 2013).

Cash transfers as a form of social assistance also appear during the Roman Empire. Before Nerva, who ruled during 96-98 AD, there were instances of money given to the citizens as a gift (Ashley, 1921). However, imperial munificence reached new heights under Nerva who established child maintenance grants-'alimenta' (Ashley, 1921).

If we trace the prevalence of cash and in-kind transfers in Islam, we find that they are instituted in Islam through Zakat- a mandatory charitable contribution-which is now most commonly given in the form of cash. The Quran provides for the levy and distribution of Zakat and specifies the purposes for which the Zakat proceeds could be expended:

"The alms are only for the poor and the needy, and those who collect them, and those whose hearts are to be reconciled, and to free the captives and the debtors, and for the cause of Allah, and (for) the wayfarer" (The Quran 9-60, translated by Pickthall, 1997).

The early Islamic state used to collect and distribute Zakat (El-Ashker & Wilson, 2006). In many Muslim countries, Zakat is still collected mandatorily.

In the modern, non-Muslim world, one of the earliest cash transfer programmes was what has become known as "Speenhamland System". In 1795, the local justices and clergymen of Speenhamland, Berkshire, UK, in response to high grain prices, decided to link the workers' wages with the bread price (creating a minimum standard of living or a subsistence level). In this system, wage top-ups or allowances-in-aid-of-wages (as Blaug (1963) calls them), were given in proportion to the price of bread and the number of children in a worker's family.

The Rationale for Cash Transfers

There is strong evidence that economic growth leads to poverty reduction. Many cross-country and cross-regional studies (e.g. Besley and Burgess, 2003; Dollar and Kraay, 2002; Ravallion and Chen, 2007) support this assertion. One, then, naturally wonders what the need of cash transfers, or direct redistribution, is. The justification for cash transfers comes from the fact that benefits of the growth do not accrue to everyone particularly the poorest. On the other hand, cash transfers, through effective targeting, may reach the poorest in a more beneficial way (Fiszbein et al., 2009).

Another justification for cash transfer is the relaxation of the liquidity constraint which can promote entrepreneurship in poor people (McKenzie & Woodruff, 2006). Lack of well-functioning markets provides another justification for cash transfers. For example, if insurance markets are not accessible to the poor, and correcting these markets is difficult, the poor cannot smooth their consumption, which cash transfers can help smooth (Fiszbein et al., 2009).

Fiszbein et al. (2009) highlight another situation where cash transfers are apt: disadvantages due to one's parents "such as race, gender, or family background", which represent inequalities of opportunity and which the state has an ethical responsibility to alleviate (Roemer, 1998).

Types of Social Transfers: Differences in Impacts and Design Considerations

A special form of cash transfers-conditional cash transfers (CCTs)-has become popular in recent decades. A CCT is a cash transfer made subject to compliance of the beneficiaries to certain conditions. Commonly, CCTs are made to poor households to incentivize them to change their behavior in terms of sending children to school, take-up services such as visits to health centres, etc. These programmes had existed since long ago, e.g. child benefits under the Family Allowances Act 1945 of the UK which provided benefits to families as long as their children were in schools. However, CCTs became popular after the success of Bolsa Escola (now, after some change in design, called Bolsa Família) programs in Brazil. Bolsa Escola programs were started in Campinas and Brasilia in the mid-90s (Sedlacek, Ilahi, & Gustafsson-wright, 2000). Later, with the introduction of Mexico's *Progresa* (later *Oportunidades* and now *Prospera*), CCTs became popular all across Latin America and other developing countries.

There are pros and cons associated with the use of CCTs and many researchers have presented arguments for and against adopting CCTs. Below we present a short review of this literature, highlighting the strengths and weaknesses of CCTs vis-à-vis in-kind transfers and unconditional cash transfers (UCTs).

The "carte-blanche" (French for "blank document") principle states that a transfer of money to a recipient is (as good as or) better[2] than an equivalent transfer of specific goods or

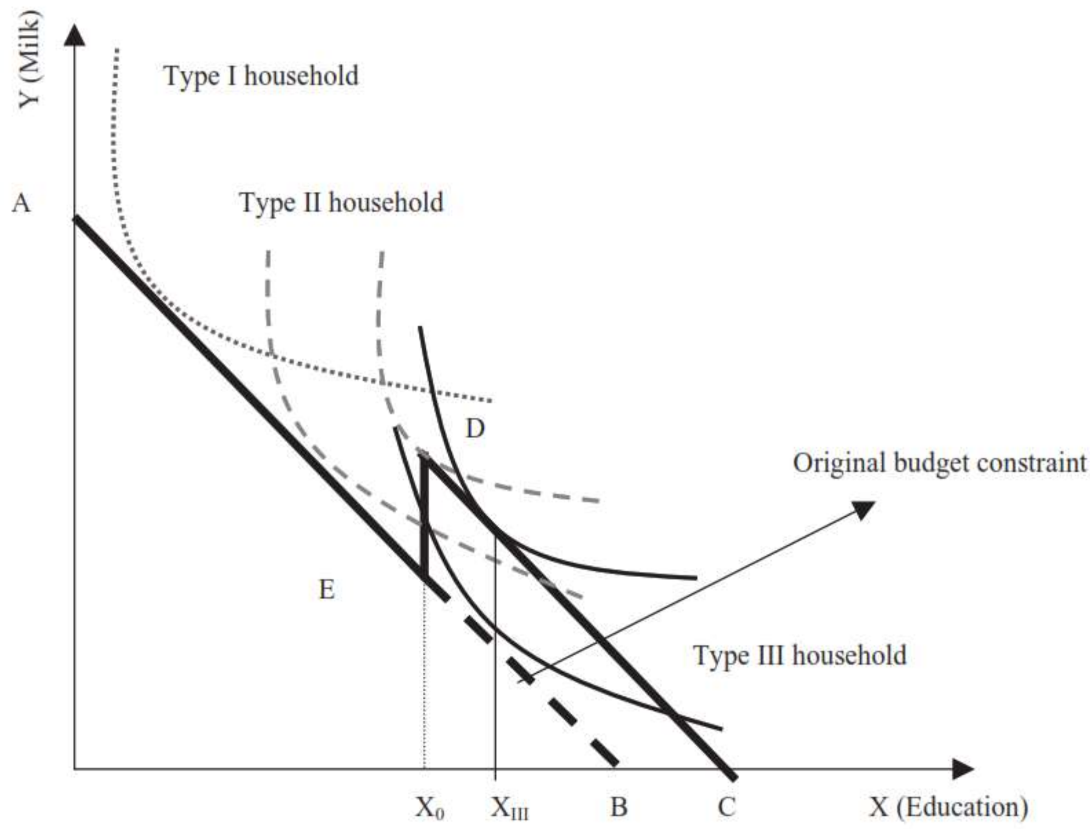
[2] More correctly, "weakly better" because consumers may be indifferent between a cash transfer and an in-kind transfer.

services (in-kind transfer and CCT[3]) to her (Pfouts, 1977). That is so because the recipient may have different preferences giving her greater utility if she were allowed to spend an equivalent amount as per her own free choice.

Besanko and Braeutigam (2014), through a graphical analysis, show that though an equivalent amount of UCT takes an individual to a higher level of utility than an in-kind transfer, the in-kind transfer induces the individual to consume more units of a good (say X) that the government wants that individual to consume. Thus, with in-kind transfers, the government can attain its objectives by spending fewer resources. So, it can be said that even if in-kind transfers are not cost-effective in terms of raising utility, they ensure that the government's objectives are fulfilled: in-kind transfers increase the consumption of X by those who would otherwise consume relatively little of that. For those persons who already consume equal or more than the government-desired level of good X, the in-kind transfer would not influence choices.

Das, Do, and Özler (2005) compare welfare effects of CCT with UCT through the following diagram.

Figure 1 Comparative Welfare Effects of CCT and UCT



Source: Das, Do, and Özler (2005)

The initial budget constraint is given by AB where a household can purchase a maximum of B of good X and A of good Y (we can assume Y is all other goods). Now, the

[3] CCTs are conceptually the same as in-kind transfers (Das, Do, and Özler, 2005). We can say that in-kind transfers are a type of conditional transfers where the transfer is made if a certain good (or service) is consumed. CCTs are analogous to the subsidies as well (Fiszbein et al., 2009).

government initiates a CCT program with the condition to consume at least X_0. Compliance to the condition gives an additional income to the household of amount ED, altering the budget constraint to AEDC. Otherwise, the old budget constraint stays put. Three types of households are shown here. Type I household (dotted indifference curve) has a preference for Y and chooses to not enrol in the program (consumes less than X_0). Type II household (dashed indifference curve) participates in the programme and complies with the condition (consumes X_0). While, type III household (solid indifference curve) has a preference toward X (pre-programme consumption of X was more than X_0) and keeps consuming the initial bundle (X_{III}).

If instead of a CCT, the government would have given a UCT of an equivalent amount, the budget line would be the line CD (it would extend and touch the y-axis). At this budget constraint, households of type I and type II would select bundles at indifference curves that are higher than the CCT case (so these households are strictly worse off with CCT). For households of type III, the indifference curves attained would be the same as in the CCT case (so they are indifferent between the two options and CCT and UCT are equivalent).

How the economic theory discussed above stacks up against empirical evidence about the differential effect of cash grants and in-kind transfers on the expenditure on a specific good? In an experiment where 1000 recipients of food stamps were randomly selected and divided into food stamp and cash recipient groups, Whitmore (2002) found that 20 to 30 percent persons belonging to the cash group spent less on food (compared to the food-stamp group) but a deeper look into their consumption pattern showed that they consumed less of soft drinks and juices. This low food consumption was not found to compromise nutrition, rather it reduced consumption of bad calories. Neither was there any indication of a difference in the consumption of alcohol amongst the cash group.

We can compute the deadweight loss of using vouchers instead of making an equivalent-value cash transfer by computing the value of both of these types of transfers to the beneficiaries. Using this approach, Whitmore (2002) found that of the 17 billion dollars expenditure on the food stamp programme, 500 million was deadweight loss (of giving stamps instead of cash). She termed this deadweight loss as the cost for political support for the programme.

The consumer theory outlined above was also vindicated by another study of United States' Food Stamps Program by Hoynes and Schanzenbach (2009), who employing difference-in-difference methods found that foods stamps were effective in increasing overall food expenditures (the out-of-pocket expenditure declined, though not in a statistically significant way). Additionally, this increase was greater for those households that had relatively low preference for food (22% increase) than for other households (15% increase). They also found that most low-income families have relatively more preference for food and their marginal propensity to consume food is similar for cash income and food stamps. Thus, there was little distortion in the consumption choices as a result of the provision of food stamps instead of a cash grant.

From the above analysis, UCTs may appear superior. However, the economic theory presented above expects individuals to be rational and well-informed and markets to be fully functional without market failures. Fiszbein et al. (2009, pp. 48-49), in the case, when these conditions are fulfilled and when the government is benevolent, declare favouring UCTs as "the "theoretical default" position". In reality, these conditions are, at least sometimes, not fulfilled and there are a few explanations why, despite the purported welfare loss caused by the in-kind and conditional cash transfers, there so many programmes of such type being implemented globally?

The classic explanation for the in-kind transfers is of paternalism (Currie & Gahvari, 2008). The argument is that the poor (or other eligible people), at least sometimes, cannot spend the cash to their or their families' greatest benefit as they do not know what is best for them or for their dependents[4] (e.g. parents not sending the children to schools[5]). On the other hand, the policymakers or the taxpayers know what is better for the poor (and the society) and hence may direct choices of the poor. There has been opposition to paternalistic views as well. Those economists who subscribe to libertarianism think that the poor, like other people, can make the best decisions for themselves (Thaler & Sunstein, 2003). Therefore, the issue if the people's choices should be constrained remains unsettled and a normative one.

Because of the targeted nature of many in-kind transfer programs and the restriction of the assistance to the goods and services thought to be really needed by the low-income groups, in-kind transfer programmes enjoy greater political support (Whitmore, 2002). Adato and Hoddinott (2007) note the same political support for CCTs because of their potential favourable impacts on education and health outcomes.

Explaining why such political support might exist, Handa and Davis (2006) opine that the political support for social assistance depends on "the values of society as well as of the characteristics of the poor" (p: 523). In countries where poverty is seen as a consequence of bad practices of individuals (e.g. low level of effort, wrong decisions) "or when the poor are easily identified as 'different'" (p: 523), social assistance would enjoy less public support. Handa and Davis (2006) cite the example of Latin America where the poor are seen as different from mainstream society. By requiring poor people to change their behaviour, CCTs allay these political concerns (Handa & Davis, 2006).

Similarly, in the United States 'individualism' leads to the perception of merit, based on productivity, and poverty is seen as a manifestation of inadequate performance (Tussing, 1974). Consequently, welfare programmes also need to have a productivity basis. A welfare regime fostering dependence is disliked because it is seen as incentivizing bad performance (Tussing, 1974), in other words, helping undeserving poor.

In the USA, in the 1960s the idea that welfare recipients could be made to attain economic self-sufficiency by providing them with the necessary social services gained currency. Ways and Means Committee of United States House of Representatives in 1962 emphasized this new "self-liquidating" model of welfare and stressed the need of providing services to help recipient families achieve self-sustenance instead of being dependent on welfare, thus obviating the need for continued public assistance (Rein, 1969). Over time, the share of in-kind transfers has risen, while unrestricted transfers have fallen (Currie & Gahvari, 2008).

By requiring the recipients to adopt a socially-responsible behaviour, CCTs foster a co-responsibility or reciprocity between the state and the citizens. This lessens the stigma associated with hand-outs and lends more dignity to the received benefits (Rawlings, 2005).

CCTs encourage human capital formation in order to break the cycle of intergenerational poverty (Rawlings, 2005, Samson, Niekerk, & Quene, 2010). In this way, in contrast to the UCTs, they focus on transient poverty (short-term income support for consumption smoothening) as well as permanent poverty (Rawlings, 2005). This combination of supporting consumption and encouraging human capital investments is seen by Ravallion (2003) as a correction for the market failures that propagate poverty. One of the market failures is the failure to internalize externalities such as education and health of

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[4] Thaler and Sunstein (2003) cite incomplete information, limited cognitive abilities, and absence of self-control as the reasons for making decisions not in one's best self-interest.

[5] This is an example of conflict of interest within the household classified by Fiszbein et al. (2009) as incomplete altruism. Such conflicts of interest may exist between the spouses as well.

children which CCTs help internalize[6] (Das, Do and Özler, 2004). However, in instances where education and health services are already significantly subsidized, using CCTs only on efficiency ground is justified only when these externalities are very large (Fiszbein, 2009).

However, there is a debate regarding whether other actions such as coupling UCTs with improvements in social service delivery would yield the same results as achieved by the CCTs (Britto, 2004). Even pure UCTs may achieve the desired social behavior. For example, if education is a normal good, increasing the income of a poor household may automatically lead to higher consumption of education services. In fact, de Carvalho Filho (2012) found that UCT to the elderly (old-age benefits) led to an increase in school enrolment of girls (particularly those aged 13–14) living with the UCT recipients (however there was little or no impact on boys' enrollment, which may suggest using other options like CCTs for boys' enrolment). This effect of UCT may be smaller than the effect of CCT of equivalent amount because CCTs have a substitution effect[7] as well besides the income effect of a pure cash transfer (Fiszbein et al., 2009).

Similarly, the same desired results could be achieved, relatively cheaply, through what is known as labelled cash transfers (LCTs). LCTs are earmarked for certain goods and services only notionally and yet they elicit the desired behavior yielding what Jacoby (2002, p. 196) dubs as "intra-household Flypaper Effect[8]" or "labeling" effect. One explanation that Hines and Thaler (1995) have given of flypaper effect is the inability to take money as fungible[9] (which represents a violation of rationality). If flypaper effects exist widely, it may be better to use UCTs instead of CCTs as UCTs would act as CCTs without having the additional costs associated with conditionalities (Fiszbein et al., 2009). However, there is not enough research available on these effects (Fiszbein et al., 2009).

Besides the potential welfare-reducing impact of the CCTs in the short run, the following additional downsides of CCTs have been pointed out.

CCTs, for their success, depend upon the availability of adequate education and health facilities (Rawlings, 2005). This may be against the interest of the poor as they often reside in the areas with poor quality of education and health services and may not be able to comply with the conditionalities and, hence, might get excluded from the CCTs (Rawlings, 2005). If facilities are not appropriate (e.g. health facilities with poor disease contamination control or schools where no or little teaching is imparted), compliance to the conditionalities may be harmful to the beneficiaries (Fiszbein et al., 2009). Even otherwise, the cost of compliance to the conditionalities is higher for the poorest and therefore they have a greater chance of exclusion from the CCTs (Samson et al., 2010).

CCTs usually have higher administrative costs (both financially as well as in terms of higher administrative capacity) due to compliance monitoring and coordination with the service providers but with the expansion of these programmes, economies of scale can be experienced (Morley & Coady, 2003).

Summing up, the choice between UCT as CCT is not an easy one. Many factors

[6] In cases such as these, social protection has efficiency arguments in its favor.

[7] Due to this substitution effect, policymakers should be wary of creating unnecessary behavior distortion e.g. by increasing goods/services use when the behavior is already optimal (Fiszbein et al, 2009).

[8] Courant, Gramlich and Rubinfeld (1979) termed the behaviour that nonmatching grants to local governments lead to comparatively higher spending by the local governments than an equivalent amount of increase in the income of the community as flypaper effect. The name follows from the fact that like a flypaper to which flies are stuck, 'money sticks where it hits' (p. 6) i.e. the government keeps the grant instead of lowering the taxes, the citizen keep their income instead of being subjected to higher taxes when their incomes increase.

[9] Thaler (1990) informs that money has labels (not fungible) because people have mental accounts of different sources of income and may have different spending patterns for each account.

discussed above need to be considered before making a choice. Fiszbein et al. (2009) also suggest using various combinations of UCTs, CCTs, and awareness provision to see how useful CCTs are.

Conceptualization of poverty and impacts of cash transfers on poverty

There is no universally accepted definition of poverty. A broad definition used by the World Bank (2000) is "poverty is pronounced deprivation in well-being" (p: 15). 'Well-being' itself refers to "whatever is assessed in an evaluation of a person's life situation or 'being'" (Gasper, 2002) or "the quality (the 'well-ness', as it were) of the person's being" (Sen, 1992). In other words, well-being is a description of a person's life situation. Various measures of well-being have been devised-some narrowed to the situation of consumption or income (such as dollar a day poverty line of the World Bank in the 1990s), and some broad enough to include other dimensions of life (e.g. education and health), most famous among which are Human Development Index (HDI) introduced in United Nations Development Programme (1990) and Multidimensional Poverty Index devised by Alkire and Foster (2011). Both HDI and MPI are inspired from the Capability Approach of Amartya Sen who first presented the idea in 1979 (Sen, 1979).

Social cash transfers immediately help improve consumption, while improvements in other aspects of well-being take some time to realize. As we do not have any recent longitudinal data available for the beneficiaries of cash transfers in Pakistan, we limit ourselves to consumption-based poverty.

A temporal classification of poverty is often made where two types of poverty are identified: i) chronic or permanent poverty, which people experience over an extended period of time, and ii) transient or temporary poverty, which people experience for short periods of time (see, e.g., Lipton & Ravallion, 1995). The transient poverty could be due to vulnerability to shocks such as income or health shocks and can push non-poor into poverty or poor into extreme poverty (Jalan & Ravallion, 2000).

How cash transfers might affect poverty? First, as shown above, they immediately relax the budget constraint, catapulting the individuals to higher indifference curves and hence higher welfare levels. This seems more relevant to address the transient poverty: income-stabilising or consumption-smoothing cash transfers will protect people from the income shocks faced by the transient poor (Lipton & Ravallion, 1995, Jalan & Ravallion, 2000; Alderman and Haque, 2006).

Second, if they are large enough, cash transfers may open the productive opportunities (e.g. education and health, etc.) for the poor (Lloyd-Sherlock, 2006; Sadoulet et al., 2001). Lipton and Ravallion (1995) point out that addressing chronic poverty would typically need policies for making the poor more productive. As discussed in the previous section, CCTs, conditional on improved choices regarding human capital, can address transient as well as permanent poverty.

Third, regular cash transfers help the poor to take up more risky alternatives thereby freeing them from low-risk low-return activities (e.g. farming low-risk crops) they partake to avoid income fluctuations (Carter & Barrett, 2006; Dercon, 2004; Lipton & Ravallion, 1995; Ravallion, 1988).

It is important to note that small cash transfers may not be able push people out of poverty (Van den Berg & Cuong, 2011). Though Devereux (2002) admits, "consumption-smoothing interventions can have mean-shifting outcomes" (p. 673), he declares the poverty impact of cash transfer "a function of the size of the transfer and its contribution to total income" (p. 666).

Selected Empirical Evidence on the Impacts of Cash Transfers on Consumption and Poverty

Cash transfers have been shown to have diverse impacts ranging from health to education to labor supply to family relations (see Fiszbein et al. (2009) for further details). However, our focus here will be on consumption-based poverty. As movement out of poverty (of the selected type) is helped by an increase in consumption, here we cover studies evaluating the impact of cash transfers directly on poverty as well as those quantifying the impacts of cash transfers on consumption. We begin with studies on the impact of cash transfers on poverty.

Agostini & Brown (2011) estimate the impact of various government cash transfers on poverty in Chile. In Chile, data on income and transfers is representative only at the regional level. However, Agostini & Brown note that due to potential geographic heterogeneity in impacts, it is important to study the effects of transfers at the county level (which is below the region level). For this purpose, they employ poverty mapping methodologies (which combine survey and census data) to find heterogeneity in the effectiveness of transfers across counties. 2003 *Encuesta de Caracterizaci´on Socioecon´omica* (CASEN) data is combined with the 2002 Chilean census. By comparing estimates of poverty before and after transfers, Agostini & Brown (2011) found that transfers lead to an economically and statistically significant reduction in headcount ratio[10] at the county level in Chile. However, these reductions are greater (ranging from 0 per cent to 67 per cent) in rural areas as compared to urban areas (where reductions range from 0 per cent to 25 per cent). These results confirm the hypothesis of heterogeneity in the impact of cash transfers on poverty. These results also imply that targeting at low levels of aggregation can lead to greater success in poverty alleviation.

Maitra and Ray (2003) using the South African Integrated Household Survey, 1994 studied the effects of private as well as public transfers on welfare. Their model allows for joint endogeneity of the expenditure shares and resource variables. They found that private, as well as, public transfers (pensions) have a significant and negative effect on poverty. They also rejected the notion of pooling of income coming from different streams and found that different sources of transfer have a differential impact on expenditures, which implies that it indeed matters who, within a household, receives the transfer.

Van den Berg and Cuong (2011) studied the impact of cash transfers on poverty in Vietnam separately for public and private transfers using Vietnam Household Living Standard Surveys (VHLSS) of 2004 and 2006. Their results indicate that public transfers had a negligible impact on poverty. On the other hand, domestic private transfers (domestic remittances) had a greater impact on poverty: they led to about 2 per cent reduction on the headcount ratio (coupled with a substantial reduction in the depth as well as the severity of poverty). The differential impact was attributed to the fact that private transfers had greater coverage of the poor and more of private transfers was used for consumption, while public transfers had low coverage and low benefit amount.

Durr-E-Nayab and Farooq (2014) evaluated the impact of Benazir Income Support Programme (BISP) on poverty using the Pakistan Panel Household Survey, 2010. They employed the Propensity Score Matching (PSM) method and found no significant difference between treated (i.e. those households which received BISP assistance) and untreated households in terms of poverty. Additionally, the magnitude of the difference was negative in some specifications and positive in other.

Cheema et al. (2016) conducted a household survey of BISP-recipient and non-recipient households to study the impact of BISP on poverty (measured using the nationally used cost-of-basic-needs approach). They used fuzzy regression discontinuity design and failed to find any statistically significant impact of BISP on poverty headcount

[10] Calculated as the number of poor divided by the total population.

ratio. Cheema et al. (2016) suggested that this lack of effectiveness was due to small benefit size of BISP cash transfer.

Azeem, Mugera and Schilizzi (2019) studied the impact of different social protection benefits in Punjab, Pakistan using Multiple Indicator Cluster Survey, 2011. They employed PSM method to compute the average treatments effects of various social protection programmes such as BISP, *Watan* card[11], *Zakat*, pensions (public and private), private financial assistance and utility stores. Azeem, Mugera and Schilizzi found that *Watan* card, public pensions, and utility stores had positive impact on expenditures while some public transfers such as BISP and Zakat had negative impact on expenditures. They attributed this lack of effectiveness to inadequate and irregular transfers under programmes such as Zakat and BISP and limited coverage of these programmes.

Skoufias, Unar and de Cossio (2015) analysed the impacts of in-kind and cash transfers under the Food Support Programme[12] in rural Mexico. The longitudinal data was collected from 5851 households in 2003-04 (baseline) and 2005 (follow-up). The programme provided food to most of its beneficiaries and cash (equivalent to 75% of the market value of the food package) to a small proportion of isolated communities where the distribution of food was difficult. An experimental design at the community level was adopted. First, 208 rural communities were selected randomly and then 33 households from each sampled community were randomly selected. These communities were then divided into two treatment (one for in-kind and one for an equivalent cash transfer) and one control groups randomly. Using the difference-in-difference approach and intention-to-treat impact estimates, the authors found that cash transfers reduced food poverty by 13.5 per cent as compared to a 15.7 per cent decrease observed for the in-kind transfer. There was no significant difference in the impacts of cash transfers (recall that they are 75% of the market price of the food package) and food transfers on food consumption. However, in the case of non-food expenditures, cash transfers have a positive impact, while in-kind transfers have no significant impact. Thus, in Skoufias et al.'s (2015) study, cash transfers seem to be more effective for increasing welfare.

Kyzyma and Williams (2017) measured the impact of various types of social transfers on the probability of rising above or falling below poverty. They used European Community Household Panel data, collected over 1994-2001 annually, and country-level transfers-related variables to capture the heterogeneity of welfare regimes. Poverty was measured in relative terms in each country (households below 60 per cent of median income were classified as poor). Kyzyma and Williams found that poverty impacts differ for different transfers: i) unemployment transfers in conjunction with effective active labor market programmes had the higher probability of helping individuals exit poverty as compared to unemployment transfers working in an environment with no active programmes; ii) unemployment benefits had a strong negative relationship with the probability of entering poverty provided that they had significant progressivity (progressivity here is the relation between the size of the transfer to the means of the beneficiary) across different quintiles of income; iii) old-age benefits had strong positive relationship with exiting poverty and strong negative relationship with the entering poverty when the benefit amount was substantial and had not much progressivity; iv) family transfers were found to have strong negative impact on poverty duration when they had little progressivity and were not liberal in benefit amount; v) Like for the case of unemployment transfers, family transfers also had stronger negative impact on the probability of entering poverty when working in an environment of supporting in-kind programmes (child care facilities).

[11] A cash transfer programme to provide flood relief.

[12] *Programa de Apoyo Alimentario* in local language.

The literature cited above has focused on the individual effects of cash transfers. Angelucci and Giorgi (2009), however, present experimental evidence using *Oportunidades* (which is a CCT) data, that cash transfers to eligible households also have a positive impact on the expenditures of other households of the community. Ineligible households' insurance and credit constraints are relaxed by receiving more loans from eligible households. Given these benefits to the overall local economy, Angelucci and Giorgi suggest doing randomization at the village level instead of individual level which may underestimate the true impacts.

However, Haushofer and Shapiro (2016) pointed out that the possibility that these spillover effects may be overestimated as in their own study, through a randomized controlled trial of a UCT in rural Kenya, they found small negative spillover effects on consumption. The UCT, which carried generous benefit (at least double of the household consumption in the covered area), was given to the poor households. Randomization levels were villages and households. Multiple treatment arms were created by randomizing gender, transfer frequency, and benefit amount. Haushofer and Shapiro found that the UCT, after nine months of its start in 2011, increased the monthly consumption expenditure of beneficiaries by a hefty 22 per cent. They also found that regular, monthly transfers enable the poor to secure their food better than infrequent transfers, which are more likely to be allocated towards the durables, (implying that poor households' savings and credit prospects are constrained). This difference between frequent and infrequent transfers has been detected by Aguila, Kapteyn, and Perez-Arce (2017) as well in a study for Mexico.

Maluccio (2010) examines the impact of a CCT in Nicaragua on expenditures using experimental methods and community-based randomisation. The results show that the CCT increased current expenditures (particularly food expenditure). However, Maluccio found only weak evidence for increases in agricultural and non-agricultural investments and hence saw limited scope for an increase in the consumption over the long run (ignoring the returns from the human capital investment that the CCT ensured).

Attanasio and Mesnard (2006) study the impact of a CCT in rural Colombia (*Familias en Acción*), which focused on health, nutrition, education, and consumption of the beneficiary households. Using the quasi-experimental method of comparing treated areas with areas not selected for the programme and using the difference-in-difference technique, Attanasio and Mesnard (2006) found that the CCT had significantly increased food consumption as well as total consumption. An analysis of the composition of expenditures showed that the CCT also led to the consumption of better quality food (particularly consumption of more proteins). Additionally, the CCT contributed to resource redistribution from adults to children by increasing expenditures on children's education and clothing.

Perova and Vakis (2012) evaluate the impacts of a CCT (*Juntos*) in Peru after five years of the start of the programme. *Juntos* distributed cash among women conditional on behaviour change related to school attendance, nutrition, and health check-ups. Perova and Vakis asked if the programme's benefit depends on the duration of the programme. They employed the instrumental-variable method and found that the impacts were higher in case of almost all of the outcomes for those beneficiaries who spent a longer time in the programme, though such differential effects were not very large. *Juntos* provided around 15 per cent of average household expenditure but led to large changes in consumption (33 per cent increase) and poverty (14 per cent reduction in the headcount ratio).

Another evaluation of *Juntos* is done by García (2017), who computed the impact of the transfer on the consumption of merit and demerit goods.[13] Using panel data from Peruvian

[13] Musgrave (1957) presented the idea of merit goods. These are goods that are thought to be good for the society and that sometimes are not consumed adequately at the individual level necessitating state's interference in consumers' preferences. Undesirable wants that have to be restricted (such as use of liquor) then become demerit goods.

National Household Survey 2009–2014, García employed the fixed-effects model to show that the programme contributed to increases in the food consumption and expenditure on children (education, clothing, footwear). There was no change in the expenditure on demerit goods (such as soft drinks, alcohol and tobacco). García credits the awareness-raising component of the programme as the factor behind higher expenditure on food and children.

Schady and Rosero (2008) assessed the impacts of a UCT on women in rural Ecuador (*Bono de Desarrollo Humano*) using a randomized design. They found that the UCT contributed to significantly larger food shares for the households in the treatment group than for those in the control group. Other studies showing increased expenditure on food or nutrient-rich food include Cunha (2014), Hoddinott and Skoufias (2004), and Macours, Schady, and Vakis (2012). Cunha (2014) also found that in-kind transfers had a greater impact on the intake of food than cash transfers.

Like Schady and Rosero (2008), some other studies have tried to investigate if the cash (or asset) transfer to women has any differential impact on expenditures and other outcomes. Hoddinott and Haddad (1995), for example, found that a greater share of wives in the cash income of the family contributed to higher food budget share. For a pension program in South Africa, Duflo (2003) also found that cash transfers improved the health and nutrition of girls (there was no effect on boys), while the same transfer to men had no such effect.

The empirical literature reviewed here generally agrees that cash transfers lead to increases in consumption (particularly food) and contribute to poverty reduction. However, the results for Pakistan (Durr-E-Nayab & Farooq, 2014 and Cheema et al., 2016) were not in line with this general trend, very encouraging in terms of the impacts of BISP on poverty reduction. Given the findings from the literature on negative impacts of cash transfers on poverty, particularly the finding by Perova and Vakis (2012) that longer duration in the programme is associated with greater impacts, it may be opportune to study the impact of BISP, which is quite old now (being born in 2008), on poverty in Pakistan. Furthermore, there is no study that has analysed the poverty impacts of BISP using the HIES 2015-16 data. The present study tries to cover this gap.

Research Design and Methodology

As the cash transfers are most commonly made to alleviate short-term and/or long-term poverty, assessing the impact of cash transfers on poverty is of natural interest. Therefore, this study aims to investigate the existence of a relationship between social cash transfers and poverty. Specifically, the research question is: Is there any impact of social cash transfers on poverty in Pakistan?

To answer the question above, i) we need to define and measure poverty and ii) find a way to measure the causal effects of the cash transfers on poverty. This chapter delineates our approach towards these two tasks.

Measurement of Poverty

As indicated earlier, in this thesis we limit ourselves to consumption based approaches to poverty. The rationale behind this choice is that we want a measure that fits in Pakistan's context and is not constrained by data availability. The government of Pakistan has officially measured poverty using three approaches: food energy intake method, cost-of-basic-needs method and MPI (Government of Pakistan, 2016a). The first two of them rely on the consumption data (more details below) that is available in the Household Integrated Economic Survey (HIES). The MPI approach relies on a broad set of data across three key human development dimensions-health, education and standard of living, represented through 10 indicators (for details, see Government of Pakistan, 2016b). The data for MPI comes from the Pakistan Standard of Living Measurement Survey (PSLM). The data on the receipts of cash transfers is available in HIES but not in PSLM, with no linkage between the two surveys. This limits our choice to consumption-based measures of poverty only as MPI cannot be calculated through HIES.

If a comparison between consumption and income is made, it has often been the opinion of researchers working on developing countries' data that consumption is better reported than income (e.g. see Deaton & Zaidi, 2002). Consumption, as compared to income, also "provides a more accurate measure of the value of the transfers to the households and thus of the welfare households are able to attain as a consequence of these transfers" (Skoufias, Unar & de Cossio, 2013, p: 407).

The Government of Pakistan (2003b) presented first-ever official estimates of poverty in Pakistan using intermittently available household surveys for the period 1986-87 to 2000-01. These estimates were based on what is known as Food Energy Intake (FEI) Method. FEI approach works through a Calorie- Expenditure Function as under[14]:

1. a minimum level of monthly calorie intake is defined for every equivalent adult[15] (call this K_{min});
2. a monthly per adult equivalent expenditure level is determined, through the regression equation (Engel curve relationship[16]) shown below, such that at the expenditure so determined the required calorie intake is barely met (call this Z)

$$\text{Ln } \hat{Z} = \hat{a} + \hat{b}\ K_{min}\ ;$$

   and
3. this expenditure level is set as the poverty line below which all households are poor.

For step one, the Government of Pakistan (2003) used the caloric intake of 2350 kilocalories per adult equivalent per day as the caloric norm (the caloric norm in urban areas is 2150 calories and 2450 calories in the rural areas). For step two, the total consumption expenditure of the bottom 60 per cent of the population was used in the regression to preclude the impact of the consumption behavior of the upper classes on the poverty line. The poverty line derived in step three was Rs. 673.54 per adult equivalent per month in 1998-99.

It is assumed that the consumption expenditure sufficient for meeting the calorie requirements (that is the expenditure equal to the poverty line) would also be sufficient for meeting the essential non-food needs. This is so because everyone, including the poorest, normally spends something on non-food items and households meeting the calorie requirements are expected to meet their non-food needs at the minimum as well.

The Government of Pakistan (2016a) reports that dissatisfaction with the official poverty numbers arose when the 2007-08 estimate of 17.2 per cent headcount ratio was met with scepticism. The estimate looked counter-intuitive given the slowdown in economic growth and increasing inflation at that time. When the new estimate (12.4 percent) for the year 2010-11 was released, the debate heightened further (Government of Pakistan, 2016a). In response to such criticism, and to capture the variation in non-food consumption in a better way, the government adopted a new methodology-called cost-of-basic-needs (CBN) approach-when the poverty numbers were released for the year 2014-15.

Poverty, on the basis of the cost of basic or minimum needs, was first measured by Rowntree (1901) who defined a basic consumption bundle and then estimated its cost. Other

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[14] This part is largely based on Government of Pakistan (2003a).

[15] A simple equivalence scale is used in which children below 18 years of age are assigned a weight of 0.8, while adults are assigned a weight of one (Government of Pakistan, 2018).

[16] Engel curve is the relationship between the nominal expenditure on (or budget share of) a particular good to total expenditures.

notable poverty measurements using minimum expenditure requirements include Beveridge (1942), Orshansky (1965) and Ravallion (1994). The approach used for official poverty measurement by the Government of Pakistan (2016a) is closely based on Ravallion (1994). The detail of the methodology adopted by the Government of Pakistan is described below[17]:

Step 1: First, a consumption aggregate is computed. The consumption aggregation requires three steps: (i) aggregation of consumption expenditure, ii) adjustment for the variation in the cost of living across different areas, and iii) adjustment for household composition. These steps are elucidated below.

(i) Aggregation of consumption expenditure: The HIES 2015-16 captures multiple types of cash and in-kind expenditures including items purchased from the market, and those received as remuneration, gifts or assistance. In the first step, a nominal aggregate of consumption is constructed by adding spending on food items and non-food items.

The values of all food items (except tobacco) consumed from every source are summed to calculate total food expenditure. For the purpose of calorie conversion, quantities are needed for every food item which for some items are not available in HIES for some households. However, in these cases, expenditures are reported, which combined with median price information from other same-cluster households yield quantities.

Non-food items include clothing and footwear, education, health, housing, utilities, transport, fuel, and recreation and communication, etc. For housing, the rental value of the residence occupied is included. This rental value comes from self-reported rent reported by renters and non-renters/owners. Only expenditures of recurrent nature are considered. Infrequent expenditures e.g. property taxes and fees, and repair and maintenance expenses are not considered. Due to data limitations precluding estimates of the value of services accrued from the durable goods, spending on durable goods is excluded from the consumption aggregate.

Some expenditures are reported in HIES on a fortnightly basis, some on a monthly basis and some other on a yearly basis. All of these expenditures are converted to a monthly basis. Values reported for fortnights are multiplied by 2.17 to arrive at monthly estimates.

(ii) Adjustment for the variation in the cost of living across different areas: Due to cost variations across the country, the nominal expenditures are adjusted by constructing a spatial price index using the Paasche formula for each primary sampling unit (PSU). The formula for the price index PI_k for psu k is[18]:

$$Pl_k = \sum_i e^{bs_i^k * \ln\left[\frac{p_i^k}{p_i}\right]}$$

where

- bs_i^k is budget share of consumption item i at the psu k
- p_k^i is the median unit value[19] for each item at the PSU-level. Both the budget shares and the median unit values are weighted by the PSU population.
- p_i is the national median unit value for each item, acting as the reference price for the index.

The calculation of unit value in the above formula implies that only items with the quantity as well as the expenditure information can be considered. Expenditure and quantity

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[17] This is based on Government of Pakistan (2018).

[18] Deaton (2003) shares this approximation of the Paasche Index:

$$lnP_P^h \approx \sum w_k^h \ln\left(\frac{p_k^h}{p_k^0}\right)$$

The index used by Government of Pakistan (2018) is a modification of this index.

[19] Unit values are used as proxies for prices and are calculated for each item as: total expenditure divided by the units consumed.

data is available in HIES for most of the food items and some non-food items. One case where expenditure and quantity information is not available for each item is when different items are reported in groups. So these have to be excluded. To ensure a meaningful contribution to the price information, only households consuming at least five different items are included.

(iii) adjustment for household composition: to account for the variation in household size and age composition that may affect consumption needs and behavior, equivalence scales are used. CBN uses the same equivalence scale as in the case of the FEI method.

Step 2: A reference group is defined (that included households that lie in the 10th to 40th percentile of the distribution of per adult equivalent consumption expenditure[20]) and the average quantity consumed of each food item by this group is taken (call this reference food basket) and multiplied by each item's median price paid by the group's households to obtain expenditure on each food item, aggregating which yields the total food expenditure (FE) on the 'reference' food basket (which captures prevailing diet patterns).

Step 3: Caloric intake given the reference basket (cal_{refgrp}) is calculated by converting the quantities into calories using a calorie conversion table and aggregating the caloric values.

Step 4: If cal_{refgrp} is lower than the required minimum level of 2350 calories per adult equivalent per day (the same caloric standard as in FEI method), FE is inflated by the ratio of the caloric requirement to cal_{refgrp} to give Food Poverty Line (FPL). Thus FPL= $\frac{\mathrm{FE}*2350}{\mathrm{cal_{refgrp}}}$.[21] Scaling-up FE ensures that each household at the FPL can meet the minimum caloric requirements.

Step 5: The average food budget share (S_f) is calculated through an iterative process with ten iterations[22]. In the first iteration, S_f is computed for those households whose food expenditure is within one per cent of the FPL. In the second iteration, this band is expanded to two per cent. In the subsequent eight iterations, the band is successively increased by 1 percentage point. The final S_f is the average of S_f of these ten iterations. This methodology of computing S_f gives more weight to the households in the initial iterations (lying closer to the FPL) as they remain part of subsequent iterations. "This is also the reason behind non-food needs being more adequately captured through the CBN method as compared to the FEI method" (Government of Pakistan, 2018, p: 16).

Step 6: The non-food component is added by inflating the FPL by S_f. Thus, the Total Poverty Line (TPL) is: TPL= $\frac{FPL}{S_f}$ [23].

There are two choices as regards the non-food expenditure level to be used for the allowance for the non-food items. Ravallion (1994) classifies them as lower and upper bounds of the poverty line. Using the non-food expenditure level of those households "who can only just afford the stipulated food bundle" (Total expenditure = FPL) gives the lower bound[24] while using the non-food expenditure level of the households who actually spend enough to meet minimum nutritional requirements (FE=FPL) gives the upper bound. The Government of Pakistan (2016b) uses this upper bound for setting its poverty line. However, S_f of the reference group households whose FE is almost equal to the FPL (instead of strict equality of FE and

[20] Exclusion of the lowest 10 percent means that consumption of population in higher brackets of consumption would be the welfare standard for the bottom ten percent population. This is said to be a more representative benchmark for poverty estimation in line with the best practice.

[21] There are some food items for some households for which only cost information is available. In this case, the information from other households where both cost and quantity of those food items are available is used to compute average cost per calorie.

[22] Wodon (1997) also uses ten iterations of this non-parametric method in his study for Bangladesh.

[23] Alternatively TPL= FPL*(1+$\frac{\text{Share of nonfood}}{S_f}$).

[24] A household that is able to meet the food requirements but chooses, instead, to spend on some non-food items must see those non-food items as the bare essentials (Ravallion, 1994).

FPL) is used for the calculations.

Why FPL is called up rather than having an objective measure of non-food expenditure is due to these reasons: i) unlike minimum energy requirements for FPL, no similar anchor is available for non-food needs, and ii) usually the price data of non-food items is either not available or is unreliable (Ravallion & Bidani, 1994).

The above methodology yielded the poverty line of Rs. 3,030.32 per month per adult equivalent using the then latest available HIES 2013-14 data, using which poverty headcount rate for Pakistan was calculated to be 29.5 per cent. For the HIES 2015-16, this poverty line was updated, using CPI inflation, to Rs. 3250.28 per adult equivalent per month (Government of Pakistan, 2018).

Methodology for Causal Impact

For establishing causality between the intervention and the outcomes, experimental methods e.g. randomised control trials (RCTs) have gained recognition as a (pseudo) gold standard. However, an RCT for the evaluation of many cash transfer programmes in Pakistan is not possible because the cash transfer programmes in Pakistan do not make randomized assignment-a necessary condition for the RCTs. Therefore, quasi-experimental methods are the second-best choice in these situations. Most popular quasi-experimental methods include difference-in-difference or double difference (DD) method, matching methods, Regression Discontinuity Design (RDD) and Instrumental Variable Design. Of these methods, we prefer matching methods as other methods have some shortfalls for our purposes. For example, the double-difference (DD) method requires baseline information of the recipient and non-recipient households, which is not available in the case of cash transfer beneficiaries in HIES. So this method is ruled out. RDD is used where a cut-off is used for the selection of the beneficiaries. The results of RDD are applicable to a sub-group of the beneficiaries around the cut-off point. Therefore, it is not desirable either. Given these constraints, we adopt matching methods.

Matching is a non-experimental method of estimating treatment effects or impacts of an intervention. It is based on the potential outcome framework (originally proposed by Fisher (1935) and exposited later by Rubin (1974)), in which every individual has a well-defined outcome for different treatment levels. Here we consider binary treatments with t = 1 showing the treatment and t = 0 indicating no treatment. For binary treatment, potential outcomes are binary as well with y_1 denoting the outcome after receiving treatment (i.e. when t=1) and y_0 is the outcome without the treatment (i.e. when t=0). As an individual *i* can, simultaneously, be in one of the treatment and control groups only, we can observe wither y_{1i} or y_{0i}, not both (implying a missing-data or missing-counterfactual problem). Matching solves this problem by comparing the outcomes of treated individuals ("participants") with those of non-treated matched individuals ("nonparticipants"). Two popular approaches of matching are covariate matching and propensity score matching. Both of these approaches match individuals on the basis of their similarity to each other in terms of observed characteristics or covariates (for example $\mathbf{x}_i = \{x_{i,1}, x_{i,2}, ..., x_{i,p}\}$ is a vector of covariates for the observation *i*). Further detail is provided in Annex-1.

There are two types of treatment effects with regard to the population being represented: average treatment effect (ATE) which considers the impacts on the overall population and the average treatment effect on the treated (ATET), which considers impacts on only those persons that are treated. The ATE estimate is given by:

$$\tau_1 = E(y_1 - y_0)$$

While, the ATET estimate is given by:

$$\delta_1 = E(y_1 - y_0 \,|\, t = 1)$$

We will use ATET in our study because most, if not all, social cash transfers in Pakistan are targeted and benefits to the non-treated households are not expected to be material.

Hoddinott, Gilligan, and Taffesse (2011) informed that NNM is generally less restrictive than PSM as "it is completely nonparametric, requiring no assumptions about the distribution of the error terms" (p: 79), while PSM requires such assumptions as it relies on the probit or logit models for computing the probabilities. NNM also does not rely on bootstrapped standard errors and, hence, has more acceptable and efficient tests of significance. However, we will employ both methods in order to see the robustness of results under the different models.

For this study, HIES 2015-16 is used as the data source. HIES 2015-16 covered 24,238 households from all across Pakistan except Federally Administered Tribal Areas and military restricted areas (hosting about two percent of the total population of Pakistan) during September, 2015-June, 2016 (Government of Pakistan, 2017). HIES contains information on household consumption by each item as well as the information on any cash transfers received by the covered households. The household consumption information is used for computing poverty using the CBN method as outlined above and the NNM and PSM techniques are used for establishing causal effects of cash transfers on poverty in Pakistan.

The calculations are performed using the software Stata 14.2.

Estimation Results

Based on the CBN approach, we calculate the headcount ratio (percentage of the population living below the poverty line or ratio of the number of the poor to the total population) using the HIES 2015-16 data. The results are reported in Table 1.

Table 1 Poverty Incidence in 2015 (Headcount Ratio-Percentages)

Rural	**Urban**	**National**
30.68	12.53	24.33

Poverty, as could be expected, is the highest in the province of Balochistan where 42 per cent of the population lives below the poverty line.

Table 2 below shows a provincial disaggregation of poverty. An interesting finding is that the province with the least headcount ratio is Khyber-Pakhtunkhwa instead of Punjab which had had this distinction over the past many years.

Table 2 Poverty Incidence by Province in 2015 (Headcount Ratio-Percentages)

Province	Balochistan	Khyber-Pakhtunkhwa	Punjab	Sindh
Headcount ratio	42.19	18.02	20.9	32.08

If we see the percentage of the population living below the first consumption quintile, the results, reproduced in Table 3, corroborate with the above findings. It is Khyber-Pakhtunkhwa which boasts the least proportion (14.52 per cent) of the population living in the bottom quintile.

Table 3 Percentage of Population in the Bottom Quintile

Province	Balochistan	Khyber-Pakhtunkhwa	Punjab	Sindh
Percentage of the population in the bottom quintile	37.33	14.52	16.45	27.65

For employing the matching methods, we need to select observable variables that correlate with the probability of programme participation and the outcome variable (poverty, in our case) but do not experience quick changes after the receipt of small cash transfers i.e. variables that are largely time-invariant (Hoddinott, Gilligan & Taffesse, 2011).

As the methodology of Proxy Means Testing relies on a strong correlation of the variables with the consumption poverty, our choice of indicators was also influenced by the indicators used in the PMT approach adopted in Pakistan as mentioned in Hou (2009). The household characteristics considered are presented in Table 4.

Table 4 Variables and their Definitions

Variable	**Definition**
Region	Shows geographical location of the household with 1=rural, and 2=urban.
Persons per room	Calculated as number of persons in a household divided by number of rooms.
Own dwelling	House owned by the household =1, Otherwise (on rent, subsidized rent, or free) = 0).
Flush toilet	Flush connected to public sewerage, pit or open drain=1, dry raised latrine, dry pit latrine or no toilet in the household=0.
Landholding	Size (in acres) of agricultural land owned by the household.
Value of livestock	Expected value (in Rs.) of currently owned animals.
Education of head	The highest grade completed by the head of the household.
No. of dependents[25]	Count of persons aged less than 18 or greater than 64.

The selected indicators were checked in terms of their correlation with poverty status. The results are given in Table 5.

[25] No. of dependents is selected instead of dependency ratio, as it had greater correlation with poverty than the dependency ratio.

Table 5 Correlation of Different Variables with Poverty Status

Variable	Pearson's Correlation Coefficient
Region	-0.223
Persons per room	0.404
Own dwelling	0.012
Flush toilet	-0.294
Landholding	-0.013
Value of livestock	0.010
Education of head	-0.248
No. of dependents	0.305

Given that own dwelling, landholding and value of livestock had a relatively low correlation with poverty status, we dropped these variables from the analysis. To confirm the relevance of these variables logistic regressions were run with the selected variables as independent variables and BISP receipt and poverty status as independent variables. The results are reproduced in Table 6.

Table 6 Relevance of Selected Variables through Logistic Regression

Dependent Variable	**BISP Receipt**		**Poverty Status**	
Parameter	Coefficient	Standard Error	Coefficient	Standard Error
Variables				
Region	-0.568*	0.801	-0.447*	0.064
Persons per room	0.167*	0.168	0.341*	0.017
Flush toilet	-0.640*	0.083	-0.868*	0.071
Education of head	-0.098*	0.009	-0.110*	0.007
No. of dependents	0.137*	0.015	0.149*	0.018
Constant	-2.092*	0.126	-1.644*	0.114
Wald chi^2 (5)	1079.26		1443.96	
Prob > chi^2	0.000		0.000	
Log pseudolikelihood	-6,423,442.6		-69,109,555	
Number of observations	24,238		24,238	

* Significant at one percent significance level.

The results from the logistic regression show that all of the selected variables significantly explain the variations in the dependent variables (BISP receipt and poverty status).

Table 7 below presents the average values of the selected variables and a few more variables of interest.

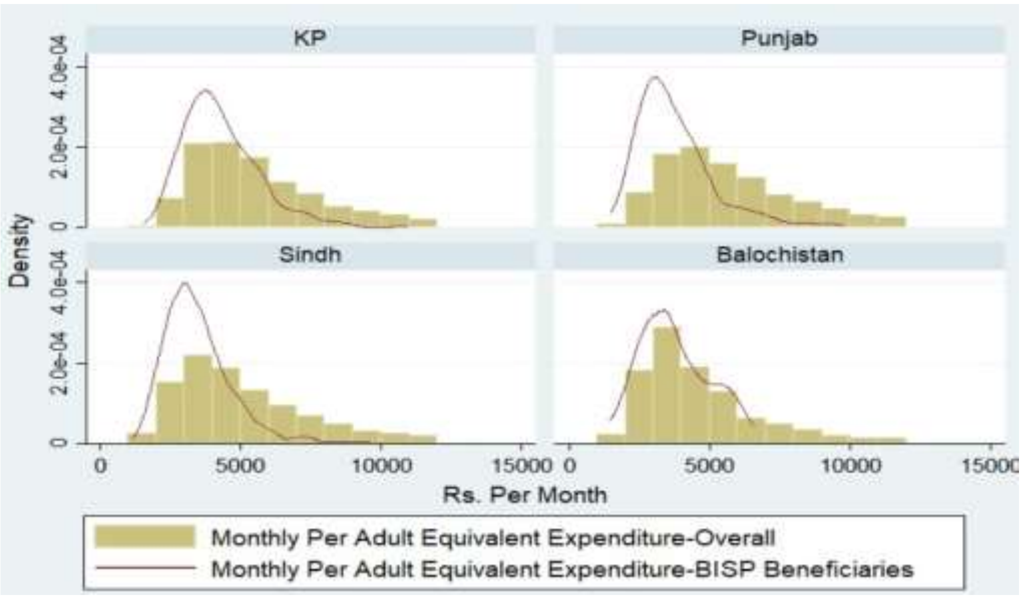
Table 7 Mean Values of Selected Variables

Variable	Non-Poor	Poor	BISP Non-Recipient	BISP Recipient	Poor and BISP Recipient
Household size	5.91	7.99	6.17	7.83	8.89
Parsons per room	2.93	5.02	3.21	4.68	5.62
Per adult equivalent monthly expenditure (Rs.)	6,824	2,688	6,237	3,714	2,591
Flush toilet	82.0%	50.0%	78.0%	49.7%	37.0%
Education of the head (years)	5.64	2.37	5.25	2.31	2.04
BISP receipt	6.0%	18.0%			
Poor			17.24%	41.19%	
No. of dependents	2.81	4.7	3.05	4.52	5.4

Table 7 shows that only 18 per cent of the poor are receiving BISP assistance, which points out to a low coverage of the programme. However, there might be some under-reporting as well because, normally, people hide their financial details from the enumerators. Another interesting finding is that of all of the BISP recipients only 41 per cent were poor considering the official poverty line. This is an indication of targeting efficiency of BISP.

Figure 2 sheds further light on targeting efficiency of BISP by comparing the distribution of per adult equivalent total expenditure of overall population (bars) and of BISP recipients (line). The line extends furthest in the province of Khyber Pakhtunkhwa indicating that comparatively richest persons from this province were enrolled in the BISP. With poverty line at Rs. 3,250.3 per month, the red line, ideally, should not extend beyond the third bar.

Figure 2 Comparison of Per Adult Equivalent Expenditure of Overall Population and BISP Recipients



Now, we report the results of the matching estimation. First, the results of our preferred method-nearest neighbor method- are reported in Table 8.

Table 8 Average Treatment Effects of BISP on Poverty

ATET Estimate	.024
Standard error	.013
P-value	.058
95% confidence interval	-.001-.050
Distance metric used	Mahalanobis
Number of observations	24,238

The results show that, contrary to the expectations from such a large cash transfer programme, BISP does not have a significant effect on poverty. The weak relationship that emerges from these results is that the BISP-recipients are marginally (two per cent) more likely to be poor than the non-recipients.

However, given the low targeting efficiency of BISP, it may be more meaningful to calculate the poverty impacts for the bottom-quintile population only. Table 9 presents the results of the nearest-neighborhood estimation with the restricted sample (bottom-quintile population only).

Table 9 Average Treatment Effects of BISP on Poverty (Bottom-quintile population)

ATET Estimate	$-4.29e^{-16}$
Standard error	$1.82e^{-17}$
P-value	0.000
95% confidence interval	$-4.65e^{-16}$ - $-3.94e^{-16}$
Distance metric used	Mahalanobis
Number of observations	3,048

The restricted sample results are encouraging and show a negative impact of BISP on poverty. The ATET estimate is significant but the effect size is so small that it is almost meaningless.

To check the robustness of the findings, we also ran a propensity score matching regression using the same variables. We tried some variation in the model to compute the propensity scores in order to check the robustness of the results by using logit as well as probit based regression. The findings are shared in Table 10.

Table 10 Average Treatment Effects of BISP on Poverty

Model	**Logit**	**Probit**
ATET estimate	.031	.026
Standard error	.013	.013
P-value	.019	.047
95% confidence interval	.005 - .057	.000 - .052
Number of observations	24,238	24,238

Compared to the full-sample nearest-neighbourhood method, the ATET estimates of PSM are significant and indicate that the BISP recipients are around three per cent more likely to be poor than the non-recipients. This surprising result, while showing that our results are not robust, also casts doubt on the performance of the BISP programme.

We also did an exercise similar to the ATET estimates with NNM. The results, shown in Table 11, remain the same in terms of direction of the effect, though the effect size becomes much smaller with the restricted sample of bottom-quintile population as compared to the full sample.

Table 11 Average Treatment Effects of BISP on Poverty (Bottom-quintile population)

Model	Logit	Probit
ATET estimate	3.26e-15	2.24e-15
Standard error	1.38e-16	9.49e-17
P-value	0.000	0.000
95% confidence interval	$2.99e^{-15}$ - $3.53e^{-15}$	$2.06e^{-15}$ - $2.43e^{-15}$
Number of observations	3,048	3,048

Conclusion and Recommendations

The estimation results based on nearest-neighbour matching method have shown that BISP has no significant impact on poverty when all population is considered and economically insignificant negative impact when the sample is restricted to the bottom-quintile population only. These results are not robust as changing the method to PSM produces different results. Our results are contrary to the evidence presented above, from multiple countries, that indicates negative effects of cash transfers on poverty (e.g. Agostini & Brown, 2011; Maitra & Ray, 2003; Van den Berg & Cuong, 2011). However, our findings fall in line with Cheema et al. (2016) and Durr-E-Nayab and Farooq (2014) who found no significant impact of BISP on poverty headcount ratio. A few explanations of our results are in order.

First, consider the benefit adequacy of the BISP cash transfer. BISP was transferring approx. Rs. 1,611 per month (BISP, 2017) to poor families[26] in 2016, the year which roughly corresponds to the data collection period of HIES 2015-16. For those poor who are receiving the BISP assistance, the benefit size becomes Rs. 205 per month per adult equivalent[27]. From Table 6 in the previous chapter, per month per adult equivalent expenditure for the poor receiving BISP assistance is Rs. 2,591, while the national poverty line is Rs. 3,250 per adult equivalent per month. If we add Rs. 205 to Rs. 2,591 the mean expenditure of the poor BISP recipient becomes Rs. 2,796, which is clearly below the poverty line and does not help the BISP beneficiary to graduate out of poverty. This relationship between low benefit amount and low impact on poverty is consistent with the literature cited above (Azeem, Mugera and Schilizzi, 2019; Cheema et al., 2016; Lloyd-Sherlock, 2006; Sadoulet et al., 2001; Van den Berg and Cuong, 2011).

Second, there might be negative labor supply effects of BISP cash transfer leading to low own-source income generation by the BISP recipients as compared to the non-recipients.

[26] The concept of a 'family' is a bit different than that of a traditional 'household' used in the household surveys in Pakistan. A family is defined by BISP as a group composed by: (i) husband, wife and their unmarried children, if any; and ii) a divorced/widowed woman and her unmarried children, if any. Thus, the presence of an ever-married woman is essential for the existence of a family. However, this difference is supposed to be immaterial for our purposes.

[27] Author's calculation.

Cheema et al. (2014) reported lower labour participation rates in males (no impact on females or overall) and attributed that to reduced labour participation by the elderly and the sick males. However, a later study by Ambler and de Brauw (2019), which partly used the same data as in Cheema et al., did not find any change in the household labor supply. A disaggregation by gender actually showed an increase in male labor supply. Though, the results of both of the studies are consistent for the overall household labour supply, the differences in the results regarding male labor supply warrant further research. Nevertheless, the small benefit size of BISP makes the expected negative labor supply effect small as well. Further research needs to be conducted to shed more light on this issue.

An interesting point on the issue of benefit size is that one might argue that the benefit size is set deliberately low in order to reduce disincentives for labour supply. Then, if a negative labour supply effect does exist, a case could be made to further reduce the benefit size. However, that could be detrimental to the interests of the poor. Therefore, a balance has to be achieved and further research needs to be conducted to establish the linkages between labour supply and BISP transfers.

Adequacy of the benefit amount also hinges on the intended objective of the programme. One may argue that graduating people out of poverty was never the objective of the UCT under BISP (the main assistance type under BISP[28]), rather it was just a measure of consumption support. However, given the effectiveness of cash transfers for poverty reduction worldwide, it is high time that the government realized the potential of BISP for graduation from poverty.

Any estimation based on household surveys gets fraught with the errors that creep in due to misreporting by the respondents. In countries like Pakistan, often people do not reveal what benefits they are receiving due to stigma associated with it or in an effort to avoid taxation. This under-reporting might be affecting our results as well. Better data capturing methods (e.g. coupling household surveys with administrative data) are needed to arrive at better results.

The targeting efficiency of 41 per cent found in our calculations also leaves a lot of room for improvement. A targeting efficiency of 41 per cent means 59 per cent of the BISP beneficiaries are non-poor (according to the official poverty line). Improving the targeting efficiency (i.e. ensuring that only poor get the assistance) might also make BISP more effective. BISP uses the Proxy Means Test (PMT) approach for the identification of the poor. This approach relies on a short set of questions regarding household demographics, housing, and assets (see Hou (2009) for more details with reference to Pakistan). However, as Kidd, Gelders, and Bailey-Athias (2017) report, the PMT approach is, by design, fraught with high inclusion and exclusion errors. Circumventing these errors through a more inclusive PMT design/cut-offs and data triangulation by using administrative data (e.g. sale and purchase of property and durables) is recommended.

Though the results related to the coverage might not be an important factor in improving the regression results that we have, improved coverage is, nonetheless, important for eliminating extreme poverty from Pakistan. The coverage of BISP is found out to be only 18 per cent i.e. only 18 per cent of the poor receive BISP benefits. This is inadequate to defeat the demon of poverty in Pakistan. It is recommended to free-up the resources from elsewhere and create fiscal space for increasing coverage of the BISP.

Another area that might warrant further research is the payment frequency of the BISP cash transfer. Currently the transfers are made after every three months. If the programme's objective is consumption smoothing, "quarterly payment for consumption smoothening" becomes an oxymoron. Consumption will be smoothed when income is smoothed as consumption depends largely on income. Haushofer and Shapiro (2016) through an RCT find,

[28] *Waseela-e-taleem*-a CCT for education of children of primary-school age was launched in late 2012.

"Monthly transfers are more likely than lump-sum transfers to improve food security, whereas lump-sum transfers are more likely to be spent on durables" (p: 1973). Given this finding, changing the BISP cash transfer payments frequency is recommended for better results in terms of poverty reduction.

Annex-1 Methodology of Nearest-neighbor Matching (NNM) and Propensity Score Matching (PSM)[29]

Nearest-neighbor Matching (NNM)

The NNM estimator was derived by Abadie and Imbens (2006, 2011). It performs covariate matching by matching each individual with the similar individual(s) from a different treatment group on the basis of a vector of covariates and uses matched individuals' outcomes for predicting the unobserved potential outcome. The 'neighbourhood' (or similarity) for the matching purpose is defined by the distance between the vectors of the covariates ($\mathbf{x}_i$ and $\mathbf{x}_j$). This distance is parameterized by the Euclidean vector norm[30]:

$$\| \mathbf{x}_i - \mathbf{x}_j \| s = \{(\mathbf{x}_i - \mathbf{x}_j)\mathbf{S}^{-1}(\mathbf{x}_i - \mathbf{x}_j)\}^{1/2}$$

where **S** is a given scaling matrix, which is symmetric and positive-definite. See StataCorp (2015) for different choices for **S**.

NNM may lead to bad matches i.e. matches with observations far apart from each other despite being the closest. To overcome this problem and improve the matching, a tolerance level is imposed on the distance, which is called a caliper (Caliendo & Kopeinig, 2008). Under this method, only individual lying within the limit specified will be selected. If there are only a limited number of matches, the estimates would have a larger variance. However, it is difficult to decide the reasonable level of caliper limit (Smith and Todd, 2005). Here we denote the caliper limit $\| \mathrm{x}_i - \mathrm{x}_j \|$, by c such that $\| \mathrm{x}_i - \mathrm{x}_j \| s \le c$.

Using the abovementioned distance functions, the set of nearest-neighbor indices for observation i becomes:

$$\Omega_m^{\mathrm{x}}(i) = \{ j_1, j_2, ..., j_{m_i} \mid t_{j_k} = 1 - t_i, \| \mathrm{x}_i - \mathrm{x}_{j_k} \| s < \| \mathrm{x}_i - \mathrm{x}_l \| s,\ t_l = 1 - t_i,\ l \ne j_k \}$$

We can choose the number of matches (m_i for the ith individual) to work with. Here m_i is the minimum number fulfilling the following condition for the number of elements in each set $m_i = |\Omega_m^{\mathrm{x}}(i)| = \sum_{j \in \Omega_m^{\mathrm{x}}(i)} w_j \ge m$[31], where w is frequency weight. The m_i may not equal m because of ties or the insufficient number of individuals falling within caliper limit of distance from the individual i.

The predicted potential outcome y_{ti} based on the observed y_i is:

$$y_{ti} = \begin{cases} y_i & \text{if} \quad t_i = t \\ \dfrac{\sum_{j \in \Omega(i)} w_j y_j}{\sum_{j \in \Omega(i)} w_j} & \text{otherwise} \end{cases}$$

[29] The details here are largely based on StataCorp (2015).

[30] A norm is a function that gives a strictly positive length to a vector.

[31] For convenience we use $\Omega(i) = \Omega_m^{\mathrm{x}}(i)$ later on.

for $t \in \{0,1\}$

The formula for the estimate ($\hat{\delta}_1$) of ATET is:

$$\hat{\delta}_1 = \frac{\sum_{i=1}^{n} t_i w_i (\hat{y}_{1i} - \hat{y}_{0i})}{\sum_{i=1}^{n} t_i w_i} = \frac{\sum_{i=1}^{n} \{t_i - (1-t_i) K_m(i)\} y_i}{\sum_{i=1}^{n} t_i w_i}$$

where

$$K_m(i) = \sum_{j=1}^{n} I\{i \in \Omega(j)\} \frac{w_j}{\sum_{k \in \Omega(j)} w_k}$$

The estimated variance of $\hat{\delta}_1$ is:

$$\hat{\sigma}_{\delta}^2 = \frac{\sum_{i=1}^{n} t_i w_i [(\hat{y}_{1i} - \hat{y}_{0i} - \hat{\delta}_1)^2 + \hat{\xi}_i^2 \{K_m^2(i) - K'_m(i)\}]}{(\sum_{i=1}^{n} t_i w_i)^2}$$

where

$$k'_m(i) = \sum_{j=1}^{n} I\{i \in \Omega(j)\} \frac{w_j}{(\sum_{k \in \Omega(j)} w_k)^2}$$

If the variance of the ATET is made conditional on the covariate information, this is called the conditional variance of the ATET estimator, which can be shown in the terms of conditional outcome variance. The conditional outcome variance for ATET estimator- $\zeta_i^2 = \mathrm{var}(y_{ti} \mid \mathrm{x}_i)$ -could be substantially smaller than the variance of ATET ($\hat{\sigma}_{\delta}^2$). If we assume ζ_i^2 to be homoscedastic (i.e. if it does not vary with the covariates or treatment), it can be calculated as:

$$\hat{\zeta}_{\delta}^2 = \frac{1}{2\sum_{i}^{n} t_i w_i} \sum_{i=1}^{n} t_i w_i \left[\frac{\sum_{j \in \Omega(i)} t_j w_j \{y_i - y_j (1-t_i) - \delta_1\}^2}{\sum_{j \in \Omega(i)} t_j w_j} \right]$$

If ζ_i^2 is heteroscedastic, the value of ζ_i^2 need to be estimated at each observation. Instead of matching on observations from different treatment groups, here matching within the same group is required.

The set of same-treatment matched individuals is:

$$\Psi_h^x(i) = \{ j_1, j_2, ..., j_{h_i} \mid t_{j_k} = t_i, \| \mathrm{x}_i - \mathrm{x}_{j_k} \| s < \| \mathrm{x}_i - \mathrm{x}_1 \| s,\ t_l = t_i,\ l \neq j_k$$

where h is the required size of the set. The number of individuals in each set, $h_i = |\Psi_h^x(i)|$, will depend on ties and the caliper limit. For convenience $\Psi(i) = \Psi_h^x(i)$ will be used.

We estimate ζ_i^2 by:

$$\hat{\zeta}^2_{t_i}(\mathbf{x}_i) = \frac{\sum_{j\in\Psi(i)} w_j (y_j - \bar{y}_{\Psi i})^2}{\sum_{j\in\Psi(i)} w_j - 1}$$

where

$$\bar{y}_{\Psi i} = \frac{\sum_{j\in\Psi(i)} w_j y_j}{\sum_{j\in\Psi(i)} w_j - 1}$$

Propensity Score Matching

The Propensity-Score Matching (PSM) method was devised by Rosenbaum and Rubin (1983) who showed that under certain conditions (discussed below) the probability of programme participation or treatment (called propensity score) can be used to solve the missing counterfactual problem and predict the treatment effects. The validity of PSM requires fulfilment of two conditions: (a) no effect of unobserved factors on the program participation (conditional independence) and (b) good common support or overlap between propensity scores of the participating (treated) and non- participating (non-treated) households (Khandker et al., 2009).

In this method, propensity scores for each individual (or household) conditional on the observed characteristics are computed and then participating and non-participating individuals are matched based on the propensity scores (matched non-participating households act as the comparison group). More formally, a treatment model (TM), $p(\mathbf{z}_i, t, \gamma)$, called a propensity score, is used to compute the probability of an individual *i* receiving treatment *t* conditional on covariates $\mathbf{z}_i$.

PSM has the advantage that multiple continuous covariates do not necessitate bias correction, rather these covariates are combined into treatment probabilities (propensity scores), thereby yielding a single continuous covariate on which matching is performed. This enables the researcher to compare different TMs in terms of goodness of fit using standard methods (e.g. information criteria) before proceeding with the nonparametric matching.

In this case, the set of nearest-neighbour indices for individual *i*, *i* = 1,…, *n*, is:

$$\Omega^p_m(i) = \{ j_1, j_2, ..., j_{m_i} \mid t_{j_k} = 1 - t_i, | p_i(t) - p_{j_k}(t) | < | p_i(t) - p_l(t) |, \ t_l = 1\text{-}t_i, \ l \neq j_k \}$$

where $p_i(t) = p(\mathrm{z}_i, t, \gamma)$ and *m* is the required number of matches. The m_i operates in the same way as in NNM with $m_i = | \Omega^p_m(i) | = \sum_{j\in\Omega^p_m(i)} w_j \leq m$.

A set of same-treatment matched individuals is (on the lines of NNM),

$$\Psi^p_h(i) = \{ j_1, j_2, ..., j_{h_i} \mid t_{j_k} = t_i, | p_i(t) - p_{j_k}(t) | < | p_i(t) - p_l(t) |, \ t_l = t_i, \ l \neq j_k \}$$

where *h* represents the required number of matches in the same-treatment group. The value of $h_i = | \Psi^p_h(i) |$ for i = 1,…, n, depends on ties and caliper's value. These sets $\Psi^p_h(i)$ will be used in the computation of standard errors for $\hat{\delta}_1$.

PSM differs with NNM in the computation of the matching set. Once the set is defined, the estimate of ATET is computed in the same way under both methods. However, the variance of the ATET estimate needs an adjustment as estimated rather than known parameters are used (γ is used instead of γ). Abadie and Imbens (2016) have derived the adjusted variance which takes the following form:

$$\sigma^2_{\delta,adj} = \sigma^2_{\delta} - \hat{\mathbf{c}}'_{\delta} \mathbf{V}_{\delta} \hat{\mathbf{c}}_{\delta} + \frac{\partial \delta_1}{\partial \gamma'} \mathbf{V}_{\gamma} \frac{\partial \delta_1}{\partial \gamma}$$

where $\mathbf{V}_{\delta}$ is the variance-covariance matrix of TM coefficients.

The adjustment term c_{δ} for the ATET estimate has two components, $\mathrm{c}_{\delta} = \mathrm{c}_{\delta,1} + \mathrm{c}_{\delta,2}$, defined as

$$\mathrm{c}_{\delta,1} = \frac{1}{\sum_{i=1}^{n} t_i w_i} \sum_{i=1}^{n} w_i \mathrm{z}_i f(\mathrm{z}'_i \gamma)(\tilde{y}_{1i} - \tilde{y}_{0i} - \delta_1)$$

$$\mathrm{c}_{\delta,2} = \frac{1}{\sum_{i=1}^{n} t_i w_i} \sum_{i=1}^{n} w_i f(\mathrm{z}'_i \gamma) \left\{ \mathrm{cov}(z_i, y_{1i}) + \frac{p_i(1)}{p_i(0)} \mathrm{cov}(\mathrm{z}_i, y_{0i}) \right\}$$

where

$$f(\mathbf{z}'_i \gamma) = \frac{dp(\mathbf{z}_i, 1, \gamma)}{d(\mathbf{z}'_i \gamma)},$$

$$\mathrm{cov}(\mathbf{z}_i, y_{ti}) = \begin{cases} \dfrac{\sum_{j \in \Psi_h(i)} w_j (\mathbf{z}_j - \bar{\mathbf{z}}_{\Psi i})(y_j - \bar{y}_{\Psi i})}{\sum_{j \in \Psi_h(i)} w_j - 1} & \mathit{if} \quad t_i = t \\[2ex] \dfrac{\sum_{j \in \Omega_h(i)} w_j (\mathbf{z}_j - \bar{\mathbf{z}}_{\Omega i})(y_j - \bar{y}_{\Omega i})}{\sum_{j \in \Omega_h(i)} w_j - 1} & \mathit{otherwise} \end{cases},$$

and

$$\tilde{y}_{ti} = \begin{cases} \dfrac{\sum_{j \in \Psi_h(-i)} w_j y_j}{\sum_{j \in \Psi_h(-i)} w_j} & \mathit{if} \quad t_i = t \\[2ex] & \mathit{otherwise} \\[2ex] \dfrac{\sum_{j \in \Omega_h} w_j y_j}{\sum_{j \in \Omega_h} w_j} & \end{cases}$$

and the sets of matched individuals within the same treatment arm, $\Psi^p_h(-i) = \Psi_h(-i)$, are:

$\Psi^p_h(-i) = \{ j_1, j_2, ..., j_{h_i} \mid j_k \neq i, t_{j_k} = t_i, | p_i - p_{j_k} | < | p_i - p_l |,\ t_l = t_i,\ l \notin \{i, j_k\} \}$

The use of the notation $\Psi_h(-i) = \Psi^p_h(-i)$ and $\Omega_h(i) = \Omega^p_h(i)$ signifies that the same- and different-treatment clusters in the calculation of $\sigma^2_{\delta,adj}$ consider *h,* not *m* used in the calculation of δ_1, although $h = m$ can be set.

The computation of $\frac{\partial \delta_1}{\partial \gamma'}$ in the formula of the adjusted variance requires additional cluster sets (denoted as $\Omega_m^{\mathbf{z}}(i)$, for i = 1,…, n.), which are made by matching on the different treatment group using the covariates $\mathrm{z}_i = (z_{i,1},..., z_{i,p})'$. The formula for $\frac{\partial \delta_1}{\partial \gamma'}$ is:

$$\frac{\partial \delta_1}{\partial \gamma'} = \frac{1}{\sum_{i=1}^{n} t_i w_i} \sum_{i=1}^{n} \mathbf{z}_i f(\mathbf{z}'\gamma) \left\{ (2t_i - 1)(y_i - \bar{y}_{\Omega_m^{\mathbf{z}} i}) - \delta_1 \right\}$$

Where

$$\bar{y}_{\Omega_m^{\mathbf{z}} i} = \frac{\sum_{j \in \Omega_m^{\mathbf{z}}(i)} w_j y_j}{\sum_{j \in \Omega_m^{\mathbf{z}}(i)} w_j}$$

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