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Targeting the Poor Secondary Students for Stipend: Identifying the Gap between Policy and Implementation

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Abstract

Well-designed and efficient poverty-based targeting methods are necessary for effectively identifying the poor households in poverty eradicating programs. This study investigates the ex-post implementation process and performance of two common targeting approaches - Proxy Means Test (PMT) and Community-Based Targeting (CBT)- to target the poor beneficiaries in a conditional cash transfer program in Bangladesh. Each method's effectiveness and implementation status was assessed using the Bangladesh Integrated Household Survey (BIHS) third round (2018-19) data in Bangladesh. Firstly, we used the probit regression model to check whether the targeting in practice follows the PMT and CBT's set of eligibility criteria. Then, we added the consumption-based poverty indicators (alternative poverty measure) and other control variables to find the other factors that might predict the selection. Secondly, we test the targeting performance using two popular targeting efficiency indicators (i.e., erroneous exclusion of the poor and erroneous inclusion of non-poor). This paper finds that although the PMT mostly followed implementation guidelines, it had high exclusion error and low coverage. In contrast, the CBT performed poorly executing the pre-defined poverty selection criteria, and the stipend selection committee used their local knowledge to identify the beneficiaries. The study also reveals that the mother's years of education and the concrete road in the community play a vital role in reducing exclusion error and increasing inclusion error under CBT. In line with other literature on this program, there were many anomalies in the selection process, and authorities should make practical implementation steps to realize the programs' full potential.

Keywords: Targeting, Conditional Cash Transfer, Poverty, Proxy Means Testing (PMT), Community-Based Targeting (CBT), Exclusion error, Inclusion error.

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1.0 Introduction

Social transfer programs to eradicate poverty must rely on efficient targeting methods to identify households in poverty and directly transfer the benefits to the beneficiary. The choice of targeting mechanism and associated targeting performance have significant implications on the efficacy of transfer programs (Stoeffler et al., 2016). According to the World Bank (2013), a targeting intervention is efficient if it essentially minimizes both exclusion of poor (i.e., exclusion error) and inclusions of non-poor (i.e., inclusion error). Thus, the poverty reduction transfer programs must accurately target impoverished households and determine how to reduce beneficiary mistargeting (Devereux et al., 2017; Sabates- Wheeler, Hurrell, & Devereux, 2015).

Many developing countries have recently adopted poverty-based Conditional Cash Transfer (CCT) programs, a popular social welfare program in which payments to households are contingent on investments in children's human capital. While designing CCT programs, policymakers should consider the countries perspective, context, and priorities to achieve measurable improvements (Schurmann, 2009). Although the conditional transfer is a component of social protection policy aimed at alleviating poverty as quickly as possible, the effectiveness of CCT programs is mixed. For example, the Mexican Progresa has achieved the most significant outcomes, whereas Bourguignon, Ferreira, and Leite (2002) find that the Brazilian Bolsa Escola has had little impact on poverty and inequality. One of the key reasons for program ineffectiveness is poor targeting of the program.

Inaccuracy in targeting can arise as a result of targeting design and targeting errors that might arise during implementation, according to Devereux et al. (2017). There is no consensus in the literature regarding which method is the most effective in each situation (Coady et al., 2004; Grosh et al., 2008). When implementing conditional cash transfers (CCTs) for low-income people or specific vulnerable groups, it is debatable how much attention was paid to the targeting. According to Fiszbein et al., 2009), Bangladesh could not target the most impoverished households and was given a higher share of benefits to the wealthier population. The reason behind this mistargeting is still unknown.

Our study examines the performance of two popular targeting methods - Proxy means testing (PMT) and community-based targeting (CBT) to target the poor beneficiaries of the Secondary Education Stipend Program (SESP) in Bangladesh. Our study uses the Bangladesh Integrated Household Survey (BIHS) third-round data developed by the USAID-funded dataset and the International Food Policy Research Institute (IFPRI).

The Proxy Means Testing (PMT) model is used to determine the poverty status, where the observable characteristics act as a proxy of income status since it is hard to determine income directly to measure poverty. In 1980, Chile's PMT approach was first introduced in the Ficha CAS program (Coady et al., 2004). Following that, this method has spread throughout Latin America and was also adopted by Mexico (Skoufias, 2001), Armenia, Indonesia (Sumarto, 2000), Egypt, and Sri Lanka. In contrast, a group of community members determines the eligibility for a program under community-based targeting (CBT) methods. In this process, program administrators generally meet the community leaders to prepare a list of poor households to formulate the agenda of program beneficiaries—for instance, the Albanian Economic Support safety net program (Alderman 2002).

In this process, PMT usually depends on consumption to create a predictor of household wellbeing, while CBT relies on community engagement. According to the World Bank, PMT is applicable for large programs with a high administrative capacity to verify eligibility and implement, but it requires regular updating of the welfare score and weights. On the other hand, CBT is appropriate for countries with insufficient administrative capacity and utilizes local information (Coady, Grosh & Hoddinott, 2004). Nevertheless, the targeting effectiveness of the program depends on the implementation team and their interest.

Khan (2014) and Schaeffing (2018) conducted a qualitative analysis on the secondary stipend program selection process in Bangladesh and observed many gray areas in the targeting process, such as the influence of local elites and stipend selection committees. Therefore, our research looked at the role of social networks in the selection process and contributed by empirically verifying their claims. Apart from that, we investigated the role of other socio-economic drivers that can predict the selection process. We followed Stoeffler, Mills, and Ninno’s (2016) methodology to identify the determinants of the exclusion and inclusion errors in Bangladesh. Although we discovered some other studies (such as Sharif, 2009) that looked at a similar program, they primarily focused on which variables and threshold levels should be used to appropriately target the poor recipients and reduce exclusion and inclusion error.

The distinctive feature of our study is that we employed a particular CCT program (in Bangladesh) using the Bangladesh Integrated Household Survey (BIHS) that had never been done before. In addition, we empirically investigated whether there is any gap between the policy and implementation and the targeting efficiency of both PMT and CBT approaches separately using exclusion and inclusion errors for the first time in Bangladesh with the secondary stipend program. This research might help to find the gap between the policy and implementation status. The results of this study may be helpful to the Bangladeshi government, particularly the Ministry of Education, in resolving the issue underlying the application of the social safety net program, which could improve the stipend program's Efficiency.

Thus, to evaluate the gap between the policy and implementation and the performance of the two targeting methods, we looked into what drives the beneficiary selection and the targeting efficiency (the exclusion and inclusion error) of the secondary stipend program. We only included students who entered secondary school between 2009 and 2018 as the CBT and PMT were implemented from 2009. This research aims to answer the following- **i)** Whether the targeting methods follow the guideline provided by authorities (Government of Bangladesh (GOB) or World Bank? If not, which factors influence the selection process? **ii)** What are the factors influencing the targeting errors, such as inclusion and exclusion errors?

2.0 Stipend Program in Bangladesh

Bangladesh is one of the most densely populated countries in South Asia, with a literacy rate of 22% for girls and 47% for boys in 1989, where the girls' gross secondary school enrollment rate was half that of boys, with a high female dropout rate of 65.9% in 1990 (World Bank, 2018). Schooling girls are more expensive than schooling boys, resulting in a substantially more significant gender disparity against girls about school enrollment in developing countries, like Bangladesh (Herz et al.,1991). Early marriage has been identified as a prevalent concern in Bangladesh by UNICEF (2006), resulting in higher school dropouts and a higher fertility rate due to a lack of socially acceptable contraception and long conjugal life. Consequently, the Government of Bangladesh (GOB) introduced a universal conditional cash transfer (CCT) program known as the Female Secondary Stipend Program (FSSP) for all female students in rural areas of the selected Upazila (i.e., sub-district) and municipality areas from 1994 to 2008. This stipend program made secondary education free for girls in rural areas by covering tuition fees and other educational costs.

This stipend was paid twice a year, while the amount varied by students' grades. The amount was deposited directly into the girl's account at the nearest Agrani Bank, a state-owned bank with branches across Bangladesh. This type of direct deposit was rare among CCT programs throughout the world since Fiszbein, and Schady's (2009) study demonstrated that most CCT were given to the head or an adult female family member. From 1994 to 2007, the stipend amount was Tk 210 for grade 6, with much higher amounts in upper grades 7,8,9, and finally Tk 970 for grade 10 (Schaeffing, A. H., 2018). To be eligible for the program, a girl must maintain a 75% school attendance rate, score at least 45% on school exams, and remain unmarried (Khandker et al., 2003).

However, Schurmann (2009) argued that the FSSP program failed to apply any effective beneficiary selection strategy, resulting in an ineffective and expensive intervention. There is a possibility that politics may drive benefits to gain influence and electoral support. According to Fiszbein et al. (2009), except for Bangladesh, most countries target the most impoverished households given a higher share of benefits than the wealthier population. This research clarifies that a higher proportion of affluent individuals are getting transfers in Bangladesh. Moreover, Fiszbein et al. (2009) estimated that the stipend amount was even less than 1% of the consumption of beneficiaries before the transfer, while in other nations, this amount ranged from 6% to 29%, indicating that the beneficiaries were receiving a relatively small transfer amount. As a result of the smaller transfer amount, the poor may have higher opportunity costs for sending their children to school (Bastagli, 2011), as transportation costs may be more than the stipend amount, or they may benefit more if their female children participate in household duties. Therefore, the poor might not participate in the program if the stipend amount is not substantially higher than the opportunity cost.

Furthermore, according to Ferranti et al., 2004, economic growth alone is insufficient to reach the poorest and alleviate poverty, and poor people cannot benefit from non-targeted CCT intervention. In this context, a targeted stipend program for the poorest would help them improve their living situations by investing in human capital development. Consequently, in 2009, the FSSP stipend program shifted to a pro-poor targeting scheme rather than sticking with a universal female targeting approach. The new program is called the Secondary Education Stipend Program (SESP) that follows entirely poor-focused objectives. Following 2009, the ADB, the GOB, and the WB dramatically raised the cash value of stipends significantly and changed the eligibility criteria. The stipend amount for grades 6 and 7 is Tk 2820, with considerably higher amounts for upper grades, resulting in Tk 5200 for grade 10 (Bangladesh Education Ministry, 2019). The program had also included boys though it is now limited to impoverished children.

In Bangladesh, currently, two targeting methods are being used in targeting for the stipend program: The Asian Development Bank (ADB) and the Government of Bangladesh (GOB) jointly use the Community-based targeting (CBT) method, whereas the World Bank (WB) uses the Proxy means testing (PMT) method. GOB and ADB jointly designed a community-based targeting approach that was used in 335 out of 460 Upazilas (i.e., subdistrict) in Bangladesh (Schaeffing, 2018).

Under the CBT method, the eligible candidates for the stipend should be the poorest 10% of boys and 30% of girls. The GOB appoints the Stipend Selection Committee (SSC) or School Management Committee (SMC) to select pro-poor students based on the following criteria: a) the household must own less than 50 decimal (A unit of area used in Bangladesh and India; 1 decimal = 436 sq feet) land, b) the household must earn less than 30,000 takas (nearly $350) per year, c) vulnerable children, such as orphans, disabled children, and autistic children, d) children of disabled parents (for example, those who are deaf, dumb, or physically disabled), e) the children of an insolvent freedom fighter, f) the child of a victim of river erosion/houseless and insolvent families, g) parents of children who work in low-wage labor (such as an Agri-day laborer), h) chronically disabled students.

However, Schaeffing (2018) assessed that the GOB became unable to create the exact measures used to target pro-poor people using the CBT process. Therefore, he discovered that the Stipend Selection Committee (SSC) did not adhere to the GoB's selection guidelines, instead of making decisions based on their assessments and preferences, making the selection process highly susceptible to nepotism, bribes, and bribes, and patronage. Khan (2014) also mentioned that the presence of "Ghost Beneficiary" in many schools and schools keeps two attendance registers, one for regular use and another for showing the stipend officials.

In contrast to the CBT method, the World Bank used its well-known proxy-means testing (PMT) tool in SESP in the remaining 125 sub-districts of Bangladesh to identify the poorest households (Schaeffing, 2018). The World Bank (WB) found the PMT method very useful in the absence of reliable income data. An algorithm followed by the PMT mechanism calculates the poverty score on pre-set indicators for household wealth (World Bank, 2005). These computed variables should have a strong correlation with household consumption and are imputed into an algorithm to determine the wealth status for each household. In Bangladesh, World Bank regularly updates the PMT model by revising the variable list with more technical accuracy (World Bank report, 2013). This process includes reducing the number of variables for easy implementation, changing the questions and question-asking patterns to minimize false reports and errors.

The PMT-driven SESP aims to classify the most vulnerable students by gathering and evaluating specific indicators of family poverty (World Bank 2017). Households below the 50th percentile PMT score are eligible for the stipend. Households are expected to fill out questionnaires at the sub-district (Upazila) office based on predetermined indicators such as land ownership, occupation, household composition, and protein consumption (Government of Bangladesh, 2011).

However, many needy families struggle to get to the office and understand the paperwork. In addition, they are excluded from the stipend scheme due to their informal job nature, irregular earnings, and inability to explain their household consumption as per pre-defined indicators. Furthermore, the staff's lack of knowledge (Khan, 2014) about program objectives, as well as their lack of assistance (Schaeffing, 2018) to households, may impede illiterate families' efforts to document their poverty. On the other hand, there was an absence of formulaic mechanisms to target an extensive portion of girl beneficiaries despite the World Bank trying to maintain a quantitative selection mechanism. It defines a lack of coordination between the program objective and the outcome of the PMT method.

3.0 Literature Review

This section presents a literature review on research relating to the Proxy means tests and community-based targeting for selecting beneficiaries in the social programs and targeting accuracy to achieve targeting efficiency. The organization is as follows; section 3.1 discusses the definitions of the two methods of PMT and CBT, their application, advantages, and disadvantages of each approach, comparison between two mechanisms; and 3.2 discusses the impact of targeting mechanism, factors affecting targeting efficiency, and targeting accuracy explaining targeting errors, the causes of targeting error and targeting inaccuracies in PMT.

3.1 PMT and CBT Approach

The Proxy means test (PMT) approach used to identify beneficiaries based on a formula that approximates household consumption using a small set of household characteristics, such as the quality of the household's residence, ownership of durable goods, adult household members' education, employment status, and demographic composition (Grosh and Baker, 1995; Grosh et al., 2008). In contrast, the community-based targeting (CBT) method relies on village members to target recipients, who are asked to rank the households based on their poverty level using wealth ranking approaches recommended by the local leaders (Coady et al. 2004; McCord 2013).

The literature on the implementation of PMT and CBT methods in social programs is vast and diverse. The implementation of PMT is more effective in Latin America for measuring household income compared to other targeting approaches (M. E. Grosh, 1994). Apart from Latin America, PMT has been implemented in several developing countries throughout the world. For example-Armenia used PMT to target cash transfers in 1994 (World Bank, 1999, 2003), Turkey adopted PMT in 2002 (Ayala, 2003), Indonesia introduced it to target rice subsidies (Sumarto et al., 2000), Pakistan and Bangladesh use it in South Asia (Sharif, 2009;

Hou, 2008). However, in practice, the process of implementing the CBT method can vary greatly. CBT, particularly easy to apply when the community is small, and members have information about each other (Coady et al., 2004). For instance, the food for education program in Bangladesh (Galasso and Ravallion, 2005) and the Albanian Economic Support safety net program (Alderman, 2002).

There is a large body of research studying the effectiveness of PMT for CCT programs. PMT method is the most favorable and cost-effective, especially when the labor market is highly informal in developing countries since it interrupts data collection on household income and expenditure levels (Coady et al., 2004; Castañeda and Lindert, 2005). For instance, due to the informal nature of the economy in Mongolia, PMT was favored over the income-based mean test, particularly among the inhabitants in rural and urban poor economies (Hodges et al., 2007). Likewise, Colombia and Egypt also use the PMT approach to identify beneficiaries in various social programs, mainly when income is difficult to access (Stephen et al., 2017). Furthermore, in distinguishing chronic poverty, the PMT tool serves as a suitable and effective targeting mechanism; hence it works well in countries like Bangladesh, where poverty severity is comparatively higher than in other South Asian countries (Grosh et al., 2008). Therefore, it can be said that PMT can more effectively target poor dwellers, as evidenced by numerous ex-ante studies of targeting in Cameroon (Stoeffler et al., 2016). This study was also validated in a few other countries. For instance, under the PMT approach, around 90 percent of social aid is gained by the bottom 40 percent of the population in Mexico and Chile (Castañeda and Lindert, 2015).

However, there is evidence of some disadvantages to implementing PMT. Kidd & Wylde (2011) observed that PMT might be expensive to administer due to high social and political costs when implementing PMT, and enumerators find difficulties checking some proxies such as age, education, household assets due to less accuracy of information from interviewees. Moreover, it is difficult to target the bottom 10% under PMT since it is hard to determine their consumption level with reasonable accuracy (Sharif, 2009). For instance, when attempting to target the bottom 10% to 20% of the population through PMT, Grosh and Baker (1995) discovered large levels of exclusion errors. This view is also supported by recent evidence from Pakistan (Hou, 2008).

On the contrary, substantial research suggests that including the community can improve targeting and project performance (Baland and Platteau, 1996; Isham et al., 1995). For instance: Subbarao et al. (1997) referred to an example of the Antyodaya program in Rajasthan in India, where the older people in the village identified the poorest ten families. Haddad and

Zeller (1996) observed that the village leaders could distinguish better between wealthy and low-income families mainly based on their living standard or income-earning potential. Having extensive knowledge of the village population may make it easier to target the current impoverished group in development programs (White and Appleton, 1999). This means that the community, rather than external agents, may play a significant role in identifying low-income households. Therefore, the CBT targeting program got more acceptance and satisfaction owing to communities' awareness of poverty (Alatas et al., 2012; Ridde et al., 2010) and their participation in the selection process (Robertson et al., 2014). Moreover, the CBT approach includes more information about the community than other approaches that follow blind criteria (Alderman, 2002). Also, CBT transfers more money than other programs (Coady et al., 2004), and the result of the CBT-driven program is progressive (Coady et al., 2004; Handa et al., 2012; Yusuf, 2010; Slater & Farrington, 2009). Besides, CBT outpaced more quantitative targeting methods in other countries evaluated by Banerjee et al. (2007).

However, when it comes to critics of CBT, we found mixed evidence. In practice, CBT has some implementation issues and community tensions noticed by Conning and Kevane (2002); Olivier de Sardan et al. (2014). Moreover, CBT causes discriminatory practices when it comes to social impact on the community, according to Haenn (1999); Slater and Farrington (2009). Likewise, Chininga (2005); Köhler et al. (2009) explained that the inconsistency of CBT with community equality preferences has also been raised. Nepotism and political ties might influence the targeting process depicted by Miller et al. (2010), Pan and Christiaensen (2011), Park and Wang (2010), while Alatas et al. (2012); Ridde et al. (2010) found no evidence of elite capture.

As a result, there is no universally ideal methodology because none of the strategies operate perfectly in certain conditions, and most studies are inconclusive to define the best method (Coady et al., 2014 & Devereux et al., 2017). According to case studies that consider targeted incidence, M. E. Grosh (1994) determined that PMT outperformed other targeting approaches. Conversely, Garcia and Moore (2012) demonstrated that CBT had been widely used because it can overcome the flaws of PMT. Some empirical studies show that CBT targeting is moderate in Sub-Saharan Africa (Sabates-Wheeler, Hurrel, and Devereux, 2014), though a similar conclusion can also be drawn for PMT targeting followed by some ex-post studies (McBride, 2014).

3.2 Targeting Efficiency and Accuracy

When deciding between PMT and CBT, a trade-off emerged between better information about the community and the possibility of elite capture in the community (Alatas et al., 2012). PMT may dominate CBT targeting when elite capture of community targeting is crucial, whereas if local information is essential, CBT might dominate PMT targeting (Alatas et al., 2012). Therefore, it is an empirical question of which method works best. However, only a few studies have examined the impact of targeting choice on the effectiveness of transfer programs. For example, Premand & Schnitzer (2018) discovered that CBT is more legitimate than PMT in Niger, while Alatas et al. (2012) found that the CBT works more efficiently in identifying the poorest households in Indonesia. Coady et al. (2004) found no difference in the performance of PMT and CBT methods after conducting a meta-analysis on 7 PMT and 14 CBT cases. Moreover, the impact of targeting method choice on the effectiveness of poverty-reducing cash transfer programs is found to be very limited (Brown et al., 2017 and Alatas, 2012).

On the other hand, the Efficiency of formula-based targeting may be affected by some other factors, such as external validity, survey accuracy, and shocks across time (Premand & Schnitzer, 2018). Survey accuracy is a concern because maintaining accuracy has become difficult because of respondent manipulation, which has been observed in some PMT targeting over time (Camacho & Conover, 2011). Another issue is external validity, as the formulas are based on samples that may or may not represent the correct program regions. As a result, Brown et al. (2016) argued that the delayed implementation of the program matters. Finally, shocks may cause concern since some household variables, such as household demography and materials, vary over time.

The targeting accuracy is poorly recorded in the literature. Ravallion (2009) assessed better targeting as an instrument that minimizes poverty, while others argued that targeting should be evaluated solely regarding the program's eligibility requirements. Targeting approaches may be related to another definition of poverty. The cash transfer program generally targets households with low consumption, implying that they are also suffering from other hardships; however, this is not the case everywhere. For example, a study conducted in Sub-Saharan Africa by Brown et al. (2017) revealed that malnourished people do not always stay in households with low consumption.

Targeting generates two forms of errors, exclusion error and inclusion error, observed by Cornia and Stewart (1995). Exclusion error includes the group of poor households who do not benefit from the program, while inclusion error consists of the nonprogram beneficiaries, interpreted by Hodges et al. (2007). However, in practice, a trade-off comes between these double errors that are unavoidable. These types of errors need to be adopted to ensure targeting accuracy. To define targeting errors in implementation, Devereux et al. (2017) stated that the rules for selecting and registering eligible program beneficiaries are not entirely satisfactory in practice. Due to poor designing of social transfer programs and errors in targeting, the beneficiaries may become more reliant on grants that necessitate evaluating social transfer programs (Slater et al., 2007). For example, an inappropriately designed education program includes all households with children, but the grant should be more meaningful if the program allows only the school-aged population. This type of erroneous targeting may create a moral hazard to the benefit of the recipients since they do not want to get out of poverty.

According to previous studies, the assessment of targeting performance is controversial once program outcome is achieved through intervention. Ravallion (2009) suggests that evaluating program outcomes rather than assessing mistargeted antipoverty programs is sufficient. However, other studies emphasized evaluating targeting effectiveness of social transfer programs (Coady et al., 2004; Devereux et al., 2017). After examining 85 programs, Coady et al. (2004) discovered that ranking programs based on targeting accuracy is not enough since it does not account for exclusion error despite combining distinct maximum scores.

The literature has highlighted the factors that may cause targeting errors, which have been discussed in a few previous studies but not extensively documented. For instance, someone who has a close connection to the official or government sector may have a higher likelihood of receiving assistance, leading to increased inclusion errors (Farrington et al., 2007). Moreover, Sharif (2009) pointed out that the urban poor is largely excluded from the program, even though the urban poor is poorer than the rural poor, raising exclusion error. While this may be true, the gap between eligible and non-eligible beneficiaries in terms of inequality is higher in urban areas than in rural areas (Akita & Pirmansah, 2011), implying that the probability of inclusion error is lower in urban areas compared to rural areas. Alatas et al. (2012) showed that the error rate is lower in urban areas if followed community-based targeting compared to PMT where there is substantial inequality and households are related.

However, Social transfer programs in Cameroon demonstrate that the PMT method captures the potential of the urban-rural disparities, signifying that it could be a better targeting method to determine the condition of the poor (Stoeffler et al., 2016). Another variable is legal identity that the government's program requires to receive social welfare benefits (World Bank, 2016). For example, the birth certificate could also be a determinant of error implementation since it indirectly relates to child rights like access to school, health, and public services (Dunning et al., 2015; Hamilton et al., 2014). According to a study conducted by Kusumawati and Kudo (2019) in Indonesian social transfer programs, targeting errors in implementation heavily rely on urban-rural disparities and legal identification rather than government employees.

In the PMT method, reducing the cut-off score helps to minimize the inclusion error but increases the exclusion error. However, after implementation, the evidence for the effectiveness of PMT is not as compelling as expected. Most of the PMT evaluations concentrate on inclusion errors. Veras et al. (2007) showed that Mexico's program (i.e., Progresa) reached 20% of the population with an estimated 70% exclusion error and 36% inclusion error. Similar evidence was also found by Brown et al. (2016) in nine African countries, where exclusion error exceeds 80% when targeting the poorest 20% and inclusion error is only about one-half. Another study of a PMT-based program in Armenia found that the rich benefited more than the poor (Kidd & Wylde, 2011). Kidd and Wylde (2011) noted that the errors are higher for the bottom 10% of the population than the bottom 20% in Bangladesh, Srilanka, Rwanda, and Indonesia. The inaccuracies in PMT targeting can be explained for a variety of reasons. However, regression only accounts for about half of the variance in household consumption described by Coady et al. (2004).

Recent empirical evidence from Bangladesh Hou (2008) and Sharif (2009) showed that many poor households are excluded from selection when targeting is imposed on less than 20% of the population where it is reduced, including non-poor households. Likewise, Kidd & Wylde (2011) pointed out that both errors increase by 46% to 61% in Bangladesh if the program size is halved. His study also exhibits that achieving inclusion and exclusion errors of less than 30% will necessitate targeting the bottom 35% to 50% of the population. Thus, balancing these errors is very crucial to fixing the cut-offs for PMT. Using a 40th percentile eligibility cut-off score and the modified PMT model, the World Bank (2013) projected an exclusion error of 32% and an inclusion error of 22% for Bangladesh (based on Household Income Expenditure Survey 2010 data).

4.0 Data and Sample

The paper relies on the Bangladesh Integrated Household Survey (BIHS) third round (2018-19) data conducted in Bangladesh. Although it is a panel survey, we could not use the first and second-round data. The first round did not include the stipend information, and the second round did not include essential variables associated with the beneficiary selection. These are nationally representative surveys and publicly available data and cover only rural areas. The third round was published in 2020. It is a USAID-funded dataset, and the International Food Policy Research Institute (IFPRI) employed it in the field.

This survey (third round) covers 5604 households in 275 primary sampling units (PSU). They applied a two-stage stratified sampling technique: firstly, selecting PSU from strata (i.e., divisions) with probability proportional to the number of households in each stratum and then, randomly selecting 20 households from each PSU (i.e., village). This dataset contains detailed information about education and exposure to the stipend program and provides a platform to analyze the targeting performance.

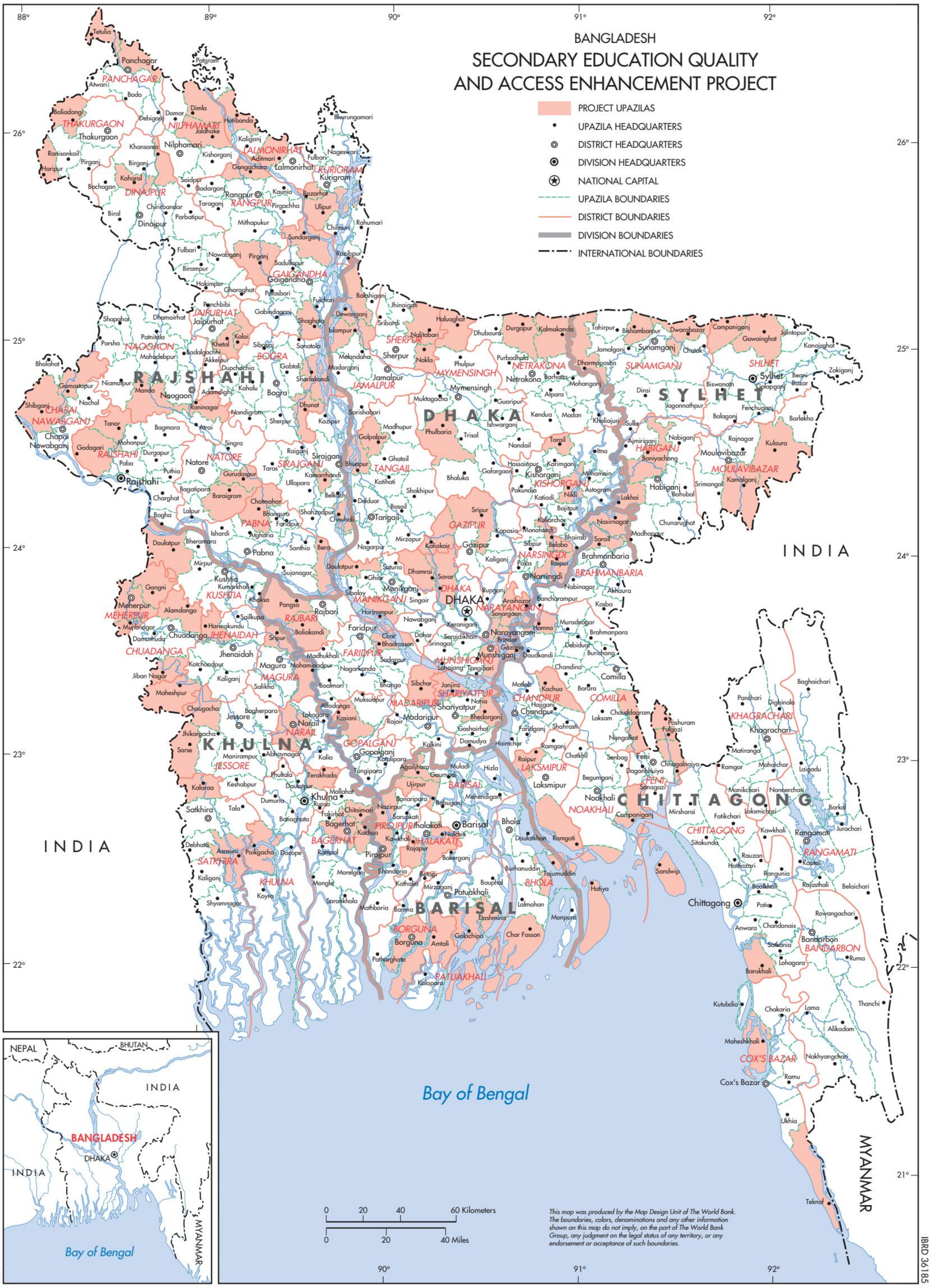
Since 2009, the World Bank and the GoB were implementing the PMT and CBT methods, respectively, all over the country. The World Bank executed the PMT program in at least one sub-district in all districts except the hilly south-eastern districts, where the government took the universal targeting approach. The government covered all other sub-districts. Thus, the households exposed by both methods are similar (Figure 1).

Since we are interested in analyzing targeting performance, we only included students born after 1996 who began secondary school in 2009 and exposed to one of the above methods. A total of 3372 children (i.e., one household might have two students) were exposed to one of these targeting methods. This dataset contains 970 children from the PMT areas and 2366 children from the CBT areas. Governments had adopted universal targeting in some hard-to-reach areas, and only 36 children came from those areas. Thus we excluded those children from the analysis.

Table 1: Number of Households by Targeting Method and Beneficiary Status

	Beneficiary (%)	Non-Beneficiary (%)	Total	Sample Status
CBT (Girls)	328 (23.9)	1,044 (76.1)	1,372	Included
CBT (Boys)	89 (8.9)	905 (91.1)	994	Included
PMT (Girls & Boys)	181 (18.7)	789 (81.3)	970	Included
Universal	8 (22.2)	28 (77.8)	36	Excluded
Total	606	2766	3372	

Figure 1: Map of PMT Areas supported by World Bank



Source: World Bank, 2008

4.1 Definition of Variables

Dependent Variables

We used two dependent variables to test the targeting performance: **beneficiary selection status** and **selection/targeting error**. If a student was awarded the secondary stipend between 2009 and 2018 by the government or World Bank, then that student was defined as a beneficiary. And then, the **beneficiary status** (1 if beneficiary and 0 otherwise) was tested with program-designated guideline variables and other controls.

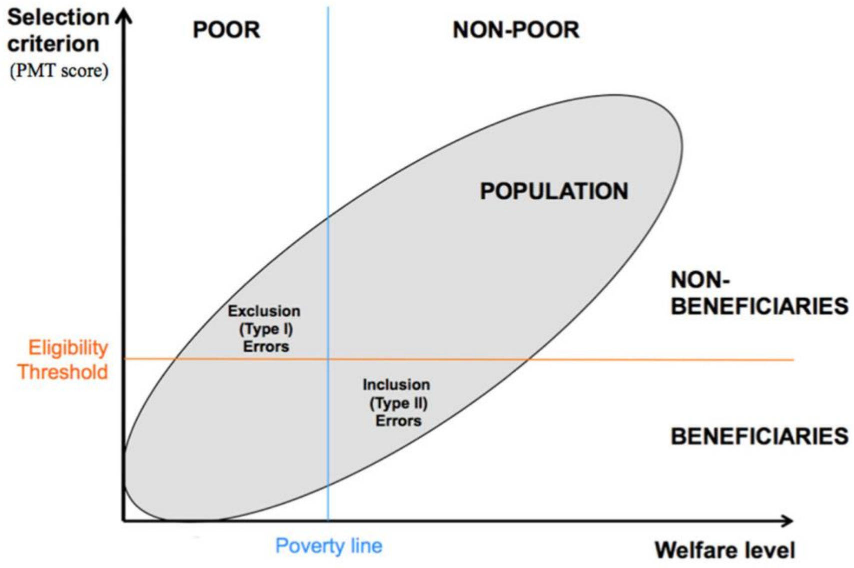
On the other hand, beneficiary selection error was measured by two indicators: exclusion and inclusion error. The **exclusion error** represents the poor eligible household erroneously excluded by the targeting method, and the **inclusion error** characterizes the non-poor household erroneously included by the targeting method. Thus exclusion error was restricted among the poor students, whereas the inclusion error was limited among the non-poor students. Thus, the error variable is 1 if the exclusion or inclusion error and 0 otherwise.

In general, we do not have specific poverty-based student ranking information calculated by the PMT score or by the CBT for judging the selection accuracy or efficiency. However, we can examine whether one student should be a beneficiary or not based on the eligibility cut-off set by GoB or World Bank and compare the selection with alternative poverty raking calculated from consumption expenditure. Following World Bank, we have calculated the consumption deciles and poverty thresholds similar to the eligibility cut-off set by the targeting method to calculate inclusion and exclusion errors by comparing selection and poverty status (World Bank, 2008).

Figure 2 and Table 2 also represent the inclusion and exclusion errors. According to the targeting method, if a consumption-based poor is a non-beneficiary, we counted that the household is erroneously excluded from the program. In contrast, if a consumption-based non-poor is a beneficiary of the program, those households are labeled as incorrect inclusion by the targeting method.

For instance, in PMT, students below the fifth consumption decile are considered in our analysis to be poor. A targeting is correct if the selected student falls below the poverty cut-off (5^{th} consumption decile). On the other hand, if a student is poor but not selected by the program, it was counted as an exclusion error, and the reverse is an inclusion error. Similarly, in CBT, a boy's household is poor if it is in the 1^{st} consumption decile, and a girl's household is poor if it is within the 3^{rd} consumption decile, and then the respective exclusion and inclusion errors are calculated for both boys and girls.

Figure 2: Interpreting the targeting performance of programs



Source: Sebastian et al., 2018

Table 2: Targeting Matrix

Beneficiary / Poverty Status	**Poor (P)**	**Non-Poor (NP)**
Beneficiary (B)	Correct Inclusion	Inclusion Error
Non-Beneficiary (NB)	Exclusion Error	Correct Exclusion

Independent Variables

Independent variables are comprised of three kinds of variables. Firstly, the guideline variables, secondly, the consumption-based poverty cut-off, and finally, the other relevant controls.

Variables for selecting the Poor by the World Bank: World Bank identified beneficiaries based on PMT score derived from the household's land ownership (0, 0-1.5 acre and more), employment status (Agri and non-Agri laborer), housing condition (wall, roof, toiler, electricity), assets (tubewell, TV, phone), years of education (head and spouse), and household size (number of adults). According to the World Bank, households who score below the 50th percentile under the PMT method are eligible for stipends and tuition waivers in Bangladesh (World Bank, 2008).

Variables for selecting the Poor by the GoB: The GoB appointed the local Stipend Section Committee (SSC) to select pro-poor students based on land ownership (below 50 decimal), low income (below 30 thousand taka), vulnerability (i.e., orphans or disabled children or children of disabled parents), shock, and low-wage labor families. Only the poorest 10% of boys and 30% of girls were eligible for the stipend (Schaeffing, 2018).

Per Capita Consumption Expenditure: Per Capita Consumption Expenditure was calculated based on food and non-food expenditure, where we only included regular expenditures and excluded the irregular expenditure such as land purchases and other annual expenditures. We have also adjusted the per capita consumption with the adult equivalence weight for children as they do not eat as much as adults (Jillian et al., 2017). We have taken the average children's weight from Jillian et al., 2017, who had calculated the adult equivalence weight for all ages of Bangladeshi people.

Consumption-Based Poverty Threshold: Like the PMT and CBT poverty threshold, we have calculated the consumption-based poverty cut-off. For instance, A boy's family is considered as poor if they are within the first decile, and a girls's family is considered as poor if they are within the third decile in the CBT areas, whereas a family is taken as poor in PMT areas if they are below the fifth decile.

Other Controls: We have also included other controls in our analysis to check whether controls can significantly explain the selection and selection error. Other control variables include household characteristics (head's and spouse's years of education, number of children and infants), living standard (solid floor, share latrine, cellphone ownership etc.), productive assets ownership (Agri assets and loan), vulnerability condition (i.e., hunger and shock), social network (i.e., school, marketplace, the union office, and concrete road with the community), and student characteristics (such as private tuition and time to reach school).

4.2 Descriptive Statistics

Household characteristics for the whole sample and by targeting methods are shown in Table 3 and Table 4. These two tables presented that the mean household size was 5, both head and spouse had about five years of education, 15.5% of households did not have any solid wall in their houses, around 75% of the respondents had taken at least one loan in their life, and 5% of the respondents did not have enough food to eat in last seven days before the survey. The respondents had on an average 108 decimal land, around 6% of them did not earn 30,000 takas ($450) annually, 12% households had at least one person of the vulnerable group such as insolvent widow and elderly, disabled person. Descriptive statistics show that around 18% of the students received the stipend. It takes on an average 23 minutes to reach school for the students, and 65% of students take at least one private tuition apart from school time.

Table 3: Socio-demographic Characteristics of households by targeting methods (Mean and Std. Dev,)

	Mean, All (Std. Dev.)	**CBT Areas** (Std. Dev.)	**PMT Areas** (Std. Dev.)
Total Consumption Expenditure (taka)	2446.83 (1456.48)	2500.00 (1531.15)	2266.45 (1195.88)
Head Age (Year)	48.27 (11.60)	48.48 (11.53)	47.78 (11.66)
Head Education (Year)	3.91 (4.06)	3.97 (4.04)	3.72 (4.12)
Spouse Education (Year)	3.78 (3.66)	3.84 (3.73)	3.64 (3.51)
Household Size	5.07 (1.97)	5.10 (1.95)	4.97 (2.00)
Number of Infant	0.37 (0.63)	0.38 (0.64)	0.35 (0.60)
Number of Children	0.97 (0.98)	0.95 (0.95)	1.02 (1.02)
Number of Adults	3.36 (1.37)	3.41 (1.39)	3.25 (1.29)
Number of Elderly (>=60 years)	0.35 (0.59)	0.35 (0.58)	0.34 (0.60)
Number of Loans	1.25 (0.98)	1.26 (0.99)	1.22 (0.96)
Time takes to reach school (minutes)	23.04 (27.05)	22.58 (22.51)	24.47 (36.01)
Total cultivable land (Decimal)	83.79 (121.77)	82.88 (117.78)	87.63 (132.31)
Total land (Decimal)	107.45 (144.28)	106.02 (135.74)	112.72 (164.70)
Value of agri asset	7683 (40491.67)	7130 (35581.04)	9190 (51081.17)
Value of total land	2697320 (4148441)	2759167 (3746188)	2620597 (5043646)

Source: Bangladesh Integrated Household Survey, 2019 (Calculated by Authors)

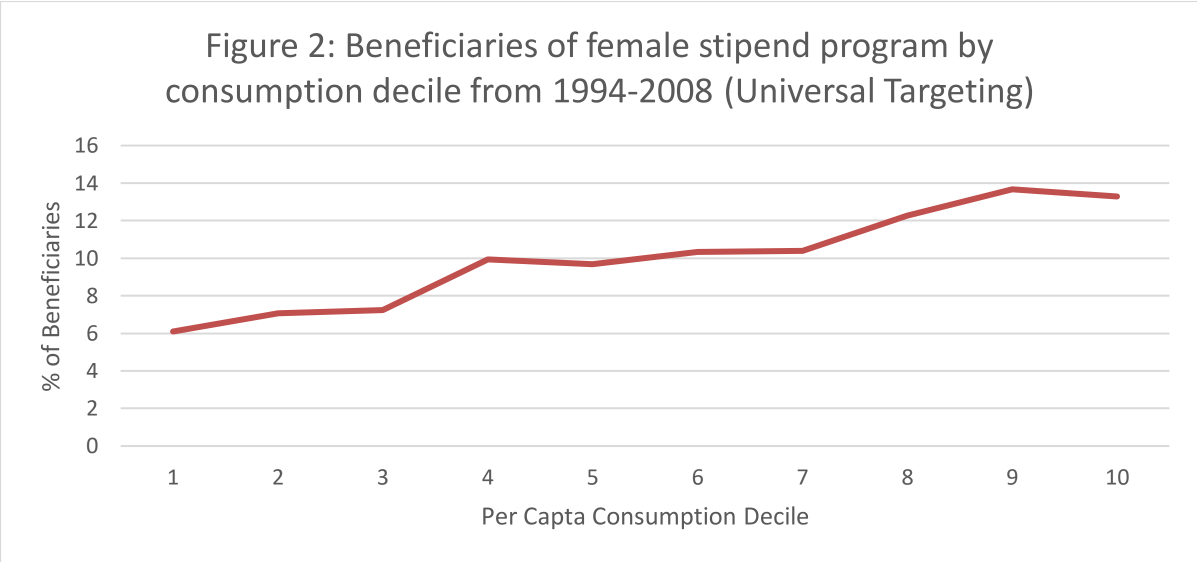
Table 4: Socio-demographic Characteristics of households by targeting methods (%)

	%, All N=3372	**CBT Area**	**PMT Areas**
Stipend Received	17.97	17.62	18.66
Secondary school in the community	30.07	29.92	29.79
Marketplace in the community	46.80	48.39	42.16
Office of union council in the community	15.30	14.71	15.57
Concrete road within community	57.44	56.30	58.66
Yearly Income<30000 tk	6.32	5.41	8.56
Vulnerable group people (insolvent widow, elderly, disabled)	11.48	11.45	11.03
Association Member	24.97	25.57	23.40
Owned of plough	9.40	9.51	9.28
Owned hand tube well	72.24	73.46	70.72
Owned shallow tube well	8.19	7.61	9.90
Owned Motor Pump	11.45	12.00	10.00
Loan	74.66	74.18	74.95
Consumption Loan	11.09	10.14	13.20
Business Loan	13.05	13.02	12.37
At least one shock in the last 3 years	55.78	54.95	57.94
Health shock	41.37	41.59	40.41
No Food to eat (last week)	4.66	5.07	3.81
Cell phone	92.59	93.07	91.55
No Solid Wall	15.45	14.33	16.39
Tin/CI/Wood Wall	52.19	51.10	55.88
Concrete Wall	32.35	34.57	27.73
Solid Floor	30.84	33.22	25.15
Concrete Roof	9.58	9.51	10.00
Separate Kitchen	93.91	94.09	93.67
No land	28.02	27.60	27.94
Upto 150 decimal	54.39	54.90	53.81
>150 decimal	17.59	17.50	18.25
Head Agri day labor	9.46	7.40	14.85
Head non-agri day labour	6.88	7.35	5.67
Own at least 3 cattle	18.59	18.43	18.45
No Electricity Connection	9.52	7.48	13.92
Bicycle	42.82	43.03	43.40
Remittance	6.23	6.76	4.95
Students get private tuition	64.45	64.06	64.76

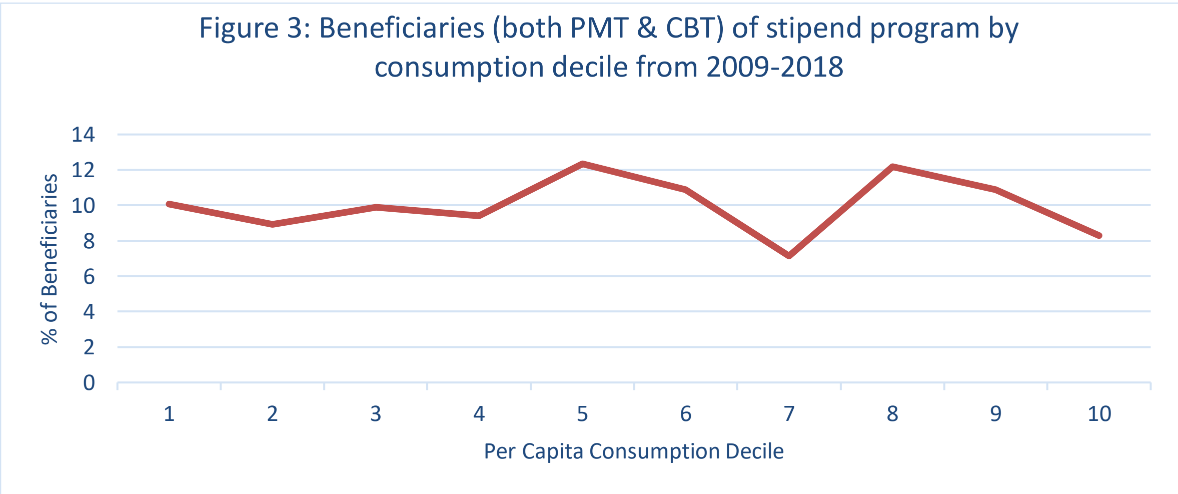
Source: Bangladesh Integrated Household Survey, 2019 (Calculated by Authors)

4.3 Variation in Selection by Consumption Group

From 1994 to around 2008, the Government of Bangladesh had targeted all girls in the rural areas for the stipend (Khandker et al., 2003). Using Bangladesh Integrated Household Survey (2019), we found that during this universal targeting period, the girls from well-off families (based on consumption expenditure) had more access to the stipend than the worse-off families (Figure 2). That finding gave an intuition that the stipend could not be accessed equally by the needy students. The program may not attract the poor students due to the stipend amount (less than $1) and their opportunity cost to work in a house or field (Mahmud, 2003).



Source: Bangladesh Integrated Household Survey, 2019 (Calculated by Authors)



Source: Bangladesh Integrated Household Survey, 2019 (Calculated by Authors)

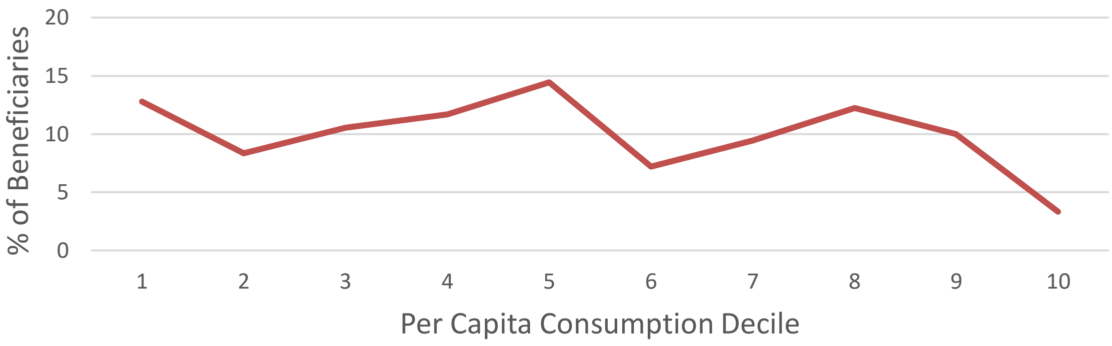


Figure 4: World Bank (PMT) beneficiaries (both girls & boys) of stipend program by consumption decile from 2009-2018

Source: Bangladesh Integrated Household Survey, 2019 (Calculated by Authors)

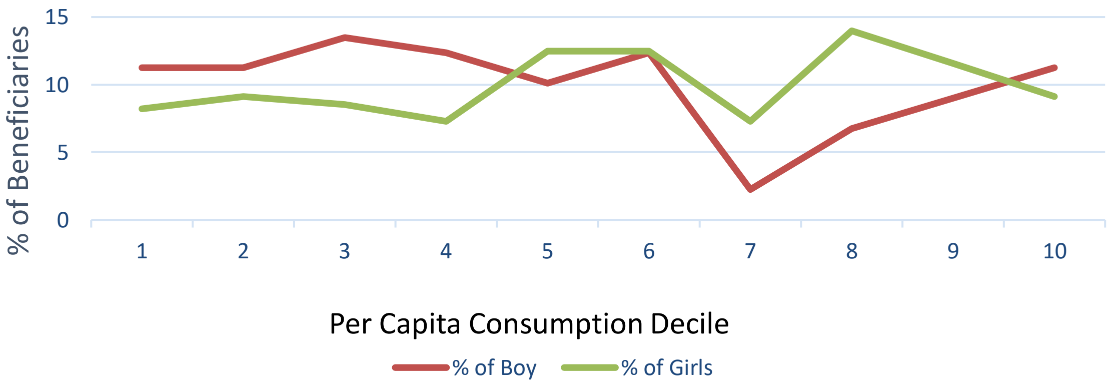


Figure 5: GoB beneficiaries (girls & Boys) of stipend program by consumption decile from 2009-2018

Source: Bangladesh Integrated Household Survey, 2019 (Calculated by Authors)

However, the Government of Bangladesh has changed its targeting policy of the secondary stipend program and introduced a poverty-targeted program for both boys and girls. Figure 3-5 shows that although only poor students (GoB Area: 30% female and 10% male and World Bank Area: below 50 percentile) should get the stipend, the students from both poor and wealthy families received the stipend, and this has occurred for both targeting methods. This finding concludes that the stipend program could not target the poor appropriately, and the program might fail to include the poor students and exclude the affluent students.

4.4 Variation in Targeting Error

Tables 5, 6, and 7 provide the status of exclusion and inclusion error, the percentage of beneficiaries covered by each targeting method, and their cumulative distribution. As mentioned above, exclusion error is calculated for only poor beneficiaries means that the poor eligible household is erroneously excluded by the targeting method and inclusion error represents non-poor households in the program who erroneously included by the targeting method.

Comparing 30% cut-off for girls and 10% cut-off for boys implemented by the CBT method and poverty status by consumption decile, we have found around 22% exclusion and 18% inclusion error in targeting the girls, whereas approximately 7% exclusion and 8% inclusion error in targeting the boys. In contrast, by assessing a 50% cut-off for implementation by PMT method and poverty status by below 5th consumption decile, we have found quite a significantly larger error, such as about 43% exclusion and 8% inclusion error.

By comparing the percentage of beneficiaries covered by the targeting method, the CBT had better coverage than PMT. The CBT method had covered around 24% of girls and 9% of boys in place of 30% girls and 10% boys, whereas the PMT coverage rate is around 19%, in contrast to the target of 50% beneficiary. This might raise the question of poor implementation of the program. Moreover, targeting literature in the context of Bangladesh mentioned the chances of "Ghost Beneficiary" within the program.

Table 5: Percentage of Inclusion and Exclusion Error

	Exclusion Error	Inclusion Error	Beneficiary Coverage (%)	
			Target	Act
CBT (Girls)	21.78	17.66	30	23.81
CBT (Boys)	6.70	7.90	10	8.90
PMT	43.19	7.97	50	18.87

Table 3 and Table 4 describes the distribution of errors created by both targeting methods. The consumption decile group (first column) represents the poverty status of the respective targeting method, and the second column shows the percentage of beneficiaries by each decile. The third and fourth column shows the distribution of exclusion (among poor) and inclusion (among non-poor) errors.

In general, the error distribution should have a higher number of errors near the threshold decile groups. The rationale behind this is: we may have different poverty measurement techniques (for instance, CBT or PMT, or Consumption), but these may not vary so much that a very rich become very poor by one poverty definition. Thus, these poor selection methods might fluctuate near the poverty threshold.

Table 6: Distribution of GoB Beneficiaries and Errors at 30th (Girls) and 10th (Boys) percentile cut-off score

	Girls			Boys		
Decile (Consumption Expenditure)	**Cumulative Distribution of Beneficiaries**	**Distribution of Exclusion Error** *21.78%=100	**Distribution of Inclusion Error** *17.66%=100	**Cumulative Distribution of Beneficiaries**	**Distribution of Exclusion Error** *6.70%=100	**Distribution of Inclusion Error** *7.90%=100
1	8.21	31.89		11.24	100	
2	9.12	33.89		11.24		12.66
3	8.51	34.22		13.48		15.19
4	7.29		9.84	12.36		13.92
5	12.46		16.80	10.11		11.39
6	12.46		16.80	12.36		13.92
7	7.29		9.84	2.25		2.53
8	13.98		18.85	6.74		7.59
9	11.55		15.57	8.99		10.13
10	9.12		12.30	11.24		12.66
Total	100.00	100.00	100.00	100.00	100.00	100.00

* Exclusion and inclusion rates from table 5
Source: Bangladesh Integrated Household Survey, 2019 (Calculated by Authors)

Table 7: Distribution of World Bank Beneficiaries and Errors at 50th percentile cut-off score

Decile (Consumption Expenditure)	**Cumulative Distribution of Beneficiaries**	**Distribution of Exclusion Error** *43.19%=100	**Distribution of Inclusion Error** *7.97%=100
1	12.78	27.18	
2	8.33	20.87	
3	10.56	18.20	
4	11.67	15.05	
5	14.44	18.69	
6	7.22		17.11
7	9.44		22.37
8	12.22		28.95
9	10.00		23.68
10	3.33		7.89
Total	100.00	100.00	100.00

* Exclusion and inclusion rates from table 5
Source: Bangladesh Integrated Household Survey, 2019 (Calculated by Authors)

However, table 6 shows that the targeting error is almost the same for the 1st to 3rd consumption decile group, and the inclusion error also did not decrease for higher deciles in GoB implementation areas. The distribution of inclusion error in the boys' segment also almost the same for all decile groups. This result creates a doubt that this program might not follow the guideline provided by the GoB. As a result, all groups of students are getting the stipend.

Although it was expected that the exclusion error would be high in the 4th and 5th decile groups and inclusion errors in the 6th and 7th decile groups, we found that both errors were spread almost equally in all decile groups (Table 7). Therefore, we may conclude that, same as the CBT; the PMT method was also implemented poorly in the field.

5.0 Methodology

This section, firstly, presented whether the targeting was implemented according to the set of targeting criteria defined by the PMT and CBT for assessing the beneficiary. Then, we employed two targeting efficiency indicators (exclusion and inclusion error) to measure the targeting performance and statistically identify which factors are responsible for targeting errors. In both of these cases, we employed the probit regression model as both of the dependent variables (i.e., beneficiary selection status [1 if beneficiary & 0 else] and error status [1 if inclusion or exclusion error & 0 else]) are binary.

5.1 Drivers of PMT and CBT Beneficiary

To evaluate whether the field staff followed the abovementioned (section 2.0) guidelines during beneficiary selection, we applied the three probit regression model for each targeting method. Firstly, we estimated a probit regression model with the guideline controls to see whether the guideline variables can explain the selection. Secondly, we added the alternative poverty definition, such as the consumption-based poverty threshold variable, to check whether the program selects the consumption-based poor households. Finally, we added other controls that might affect the selection process. In all the cases, the dependent variable is selection status (i.e., beneficiary or not). If a student i's selection by the method j (PMT or CBT) is defined by $s_{ij} = 1$, then the model is

$$Pr\left(s_{ij} = 1 \middle| X_i\right) = \varphi\left(\beta_j X_i + \varepsilon_{ij}\right), i \epsilon\ P\ \&\ NP \ldots \ldots \ldots (1)$$

where P means the Poor and NP means the Non-Poor student. We reported the marginal effect of the probit model in the result.

5.2 Drivers of Targeting Efficiency

We estimated the probit regression model to determine the inclusion and exclusion error factors by PMT and CBT method. This model measures the likelihood of the poor households incorrectly being excluded by CBT and PMT methods and the likelihood that non-poor households are incorrectly included.

At first, we specified a model to estimate the household characteristics and other control (such as social network, shock, and student characteristics) connected with the erroneous exclusion. If a household i is incorrectly excluded by a method j (CBT/PMT) when s/he is eligible for the program, then the exclusion error is defined as $ee_{ij} = 1$. Thus the model is:

$$Pr\left(ee_{ij} = 1 \middle| X_i\right) = \varphi\left(\beta_j X_i + \varepsilon_{ij}\right), i \in P \ldots\ldots\ldots (2)$$

where X_i represent the vector of household characteristics and other controls, ε_{ij} imply the error term, and P indicates students from poor households. This regression is conducted among the poor households in the sample as they are only excluded from the program.

Similarly, we estimated a model for the erroneous inclusion, where a household i is incorrectly included by a method j (CBT/PMT) when s/he is not eligible for the program, then the inclusion error is defined as $ie_{ij} = 1$. The model is

$$Pr\left(ie_{ij} = 1 \middle| X_i\right) = \varphi\left(\beta_j X_i + \varepsilon_{ij}\right), i \in NP \ldots\ldots\ldots (3)$$

where NP indicates the students from the non-poor households. This regression is conducted among the non-poor households in the sample as they are only included in the program. We reported the marginal effect of the probit model in the result.

5.3 Other Issues

Standard Error and Regional Fixed Effect: The observations are clustered into village-level, and so, we expect that the errors from the households of the same village could be correlated while independent across the village. Additionally, we used division-level fixed effects for model estimation. Moreover, we have used backward, forward, and Lasso selection techniques to find the control variables that can explain the variations in the dependent variables.

Omitted Variable and Causality: As some key variables determining the beneficiary selection might be missing in the dataset, we might have omitted variable bias. For instance, Khan (2004) mentioned that some external factors such as political interference, power misuse by stipend selection committee or school management committee, and relationship with the student could influence the selection, but these are not available in the dataset. Also, the cross-sectional data do not allow controlling for unobservable variables. Thus, we can neither deny the endogeneity nor claim for causal inference.

Robustness Analysis: We checked the robustness of the results by using the alternative functional form (i.e., Linear Probability Model) and specification, where we included PMT score and log of per capita consumption expenditure to find the factors affecting the targeting after the inclusion poverty scores (Appendix).

6.0 Results and Discussion

6.1 Evaluating the Implementation of Targeting Guidelines

The result from the probit regressions to determine whether the field staff followed the GoB and World Bank guidelines has three parts: only with guideline variables, guideline and poverty cut-off, and guideline and other controls). Table 8 shows the results from estimation equation 1 (but the marginal effects are reported) for the girls in the CBT implementation areas. The first column reports that the CBT guideline variables are not correlated with the community selection. Even after adding the alternative poverty definition, such as the consumption-based poverty cut-off variable (2nd column), we can see that this variable is insignificant with all CBT guideline-based variables. However, after adding other controls (3rd column), only one CBT guideline-based variable is significant (i.e., Head Agri-labour), whereas other control variables unrelated to guidelines can significantly predict the selection.

This might give us a sign that although there was a policy for selecting the poor students with pre-defined guidelines, the field office did not monitor the selection process, and the stipend selection committee took advantage of that to choose according to their judgment. According to Schaeffing (2018), the selection process is also highly susceptible to nepotism, bribes, and patronage. The positive correlation and Statistical Significance of the one network variable also support this finding.

The regression result in the third column shows that the probability of selection by CBT increases with head's agri-based labor, spouse education, households with two infants, those who have concrete roads within the community, and those students who need more time to reach school. On the other hand, the probability of CBT selection decreases with a solid floor, shared latrine, and motor pump ownership. Surprisingly, the consumption expenditure-based poverty cut-off variable was insignificant in both 2nd and 3rd specifications. These results might reflect the situation of poor implementation of selection appropriate beneficiary in practice.

Table 8: Marginal Effect of Determining the CBT-Girls Selection

VARIABLES	(1) CBT Guideline	(2) CBT Guideline & GoB Poor cut-off	(3) CBT Guideline & Other Controls
CBT Guideline			
Land below 50 Decimal	-0.015 (0.025)	-0.021 (0.025)	-0.024 (0.029)
Yearly Income<30000	0.059 (0.049)	0.065 (0.050)	0.054 (0.069)
Vulnerable Group	0.028 (0.038)	0.036 (0.038)	0.009 (0.041)
Head Agri. Day Laborer	0.046 (0.046)	0.060 (0.046)	**0.099** (0.045)**
Head Non-Agri. Day Laborer	0.050 (0.042)	0.048 (0.042)	0.035 (0.041)
Non-Head Agri. Day Laborer in HH	0.061 (0.057)	0.065 (0.057)	0.051 (0.057)
Non-Head Non-Agri. Day Laborer in HH	-0.012 (0.042)	-0.013 (0.042)	0.006 (0.046)
At least 1 Shock in last 3 years	0.009 (0.025)	0.010 (0.024)	-0.016 (0.041)
Below 3rd Consumption Decile Threshold		-0.051 (0.031)	-0.043 (0.034)
Household Characteristics			
Head Education in Years			-0.004 (0.004)
Spouse Education in Years			**0.014*** (0.004)**
One Infant			0.004 (0.027)
Two Infants			**0.134** (0.060)**
Living Standard			
Owned Cellphone			0.015 (0.058)
Owned Bicycle			0.027 (0.028)
Solid Floor			-0.043 (0.032)
Share Latrine			**-0.102***(0.037)**
Productive Assets			
Owned Pesticide Sprayer			0.042 (0.034)
Owned Motor Pump			**-0.110**(0.048)**
Vulnerable Condition			
At least 1 Health Shock after 2015			0.047 (0.042)
No Food to Eat			-0.061 (0.072)
Social Network			
Secondary School within the Community			0.058 (0.036)
Marketplace within the Community			-0.006 (0.032)
Union Office within the Community			-0.004 (0.047)
Concrete Road within the Community			**0.101*** (0.031)**
Association Leader			-0.092 (0.059)
Student Characteristics			
Students receive any private coaching			-0.013 (0.019)
Time to reach school			**0.002***(0.001)**
Divisional Fixed Effect	Yes	Yes	Yes
Observations	1,372	1,372	1,054

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 9: Marginal Effect of Determining the CBT-Boys Selection

VARIABLES	(1) CBT Guideline	(2) CBT Guideline & GoB Poor	(3) CBT Guideline & Other Controls
CBT Guideline			
Land below 50 Decimal	0.014 (0.018)	0.016 (0.018)	0.022 (0.022)
Yearly income<30000	0.008 (0.034)	0.009 (0.034)	**-0.126*(0.065)**
Vulnerable Group	**0.073***(0.025)**	**0.073***(0.025)**	**0.067**(0.028)**
Head Agri. Day Laborer	0.046 (0.033)	0.040 (0.032)	0.045 (0.035)
Head Non-Agri. Day Laborer	0.021 (0.032)	0.021 (0.032)	-0.001 (0.033)
Non-Head Agri. Day Laborer in HH	0.011 (0.050)	0.009 (0.050)	0.043 (0.046)
Non-Head Non-Agri. Day Laborer in HH	-0.016 (0.035)	-0.018 (0.035)	0.014 (0.037)
At least 1 shock after 2015	0.005 (0.019)	0.004 (0.019)	-0.018 (0.033)
Below 1st Consumption Decile Threshold		0.035 (0.034)	0.032 (0.036)
Household Characteristics			
Head Education in Years			0.003 (0.003)
Spouse Education in Years			**0.006* (0.004)**
1 Children			-0.030 (0.021)
2 Children			-0.017 (0.024)
3&+ Children			**-0.071**(0.033)**
Living Standard			
Cellphone			**-0.079**(0.035)**
Owned Bicycle			0.019 (0.023)
At least 1 Consumption Loan			0.058*(0.031)
Solid Floor			-0.004 (0.024)
Share Latrine			-0.003 (0.029)
Productive Assets			
Owned Pesticide Sprayer			0.023 (0.025)
Own Motor Pump			-0.023 (0.040)
At least 1 Agri Loan			0.034 (0.029)
Vulnerable Condition			
No Food to Eat			0.059 (0.041)
At least 1 health shock after 2015			0.0001 (0.034)
Social Network			
Secondary School within Community			0.007 (0.028)
Bazar within Community			-0.006 (0.025)
Union Office within Community			-0.039 (0.039)
Concrete Road within Community			-0.011 (0.022)
Association Leader			0.008 (0.035)
Student Specific Variable			
Students receive any private coaching			**0.033**(0.013)**
Time to reach school			-0.0004 (0.001)
Divisional Fixed Effect	Yes	Yes	Yes
Observations	994	994	784

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 10: Marginal Effect of Determining the PMT Selection

VARIABLES	(1) PMT Guideline	(2) PMT Guideline & PMT Poor	(3) PMT Guideline & Other Controls
PMT Guideline			
Total Agri Land: Upto 1.5 Acres	0.031 (0.031)	0.030 (0.034)	0.024 (0.035)
Total Agri Land: More than 1.5 Acres	0.057 (0.046)	0.057 (0.046)	0.047 (0.051)
Head Agriculture Day Laborer	**0.069*(0.039)**	**0.069* (0.039)**	0.059 (0.041)
Head Non-Agri. Day Laborer	**0.122**(0.057)**	**0.121**(0.058)**	**0.131**(0.062)**
Non-Head Agri. Day Laborer in HH	-0.017 (0.045)	-0.017 (0.046)	-0.012 (0.044)
Non-Head Non-Agri. Day Laborer in HH	-0.090 (0.069)	-0.090 (0.070)	-0.104 (0.068)
Own at least 3 Cattles	0.015 (0.038)	0.015 (0.038)	0.014 (0.037)
Solid Wall: Tin/CI/Wood	**-0.085**(0.039)**	**-0.086**(0.039)**	**-0.088**(0.038)**
Solid Wall: Mud	-0.035 (0.045)	-0.035 (0.045)	-0.048 (0.045)
Wall: Bamboo/straw/leaf	-0.022 (0.069)	-0.023 (0.069)	0.011 (0.069)
Concrete Roof	0.031 (0.046)	0.031 (0.0471)	0.014 (0.047)
Own Tube Well	0.018 (0.028)	0.019 (0.029)	0.013 (0.028)
No Electricity Connection	-0.029 (0.047)	-0.029 (0.047)	-0.036 (0.046)
Owned TV	-0.0003 (0.034)	0.0005 (0.034)	-0.012 (0.034)
Owned Bicycle	-0.047 (0.0367)	-0.047 (0.037)	-0.047 (0.036)
Number of Rooms: 2-3	-0.025 (0.039)	-0.025 (0.040)	-0.023 (0.041)
Number of Rooms: 4&+	0.210 (0.164)	0.211 (0.164)	0.211 (0.174)
Number of Children: 2/3 Childs	**-0.063* (0.033)**	**-0.063* (0.033)**	**-0.067**(0.033)**
Number of Children: 4&+ Childs	-0.035 (0.042)	-0.035 (0.042)	-0.051 (0.041)
Number of total households	**0.018**(0.009)**	**0.018**(0.009)**	**0.016*(0.009)**
Head Education Level: 5-9 Years	-0.022 (0.036)	-0.022 (0.036)	-0.027 (0.036)
Head Education Level: 10-12 Years	0.019 (0.052)	0.020 (0.053)	0.029 (0.053)
Head Education Level:12+ Years	**-0.142*** (0.035)**	**-0.141***(0.035)**	**-0.139***(0.034)**
Spouse Education Level: 10&+ Years	0.009 (0.068)	0.010 (0.068)	0.003 (0.061)
Remittance from Abroad	-0.138 (0.096)	-0.138 (0.096)	-0.120 (0.092)
Below 5th Consumption Decile Threshold		0.004 (0.030)	0.005 (0.031)
Productive Assets			
Own Weeding Tool			0.046 (0.029)
Own shallow Tube well			-0.058 (0.048)
Number of Loan Taken:1 Loan			0.043 (0.037)
Number of Loan Taken: 2 Loans			0.033 (0.044)
Number of Loan Taken: 3&+ Loans			**0.134** (0.058)**
Vulnerable Condition			
No Food to Eat			-0.073 (0.070)
Social Network			
Secondary School within Community			-0.021 (0.036)
Marketplace within Community			0.045 (0.031)
Union Office within Community			-0.064 (0.041)
Concrete Road within Community			0.024 (0.027)
Association Member			-0.041 (0.032)
Divisional Fixed Effect	Yes	Yes	Yes
Observations	796	781	781

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

In boys' selection by CBT, only two guideline variables are positively significant for all three specifications, whereas others don't. Apart from the guideline variables, the likelihood of selecting beneficiaries increases with spouse education and children's private tuition. In general, the school teachers are given private tuitions in rural areas of Bangladesh, and some of these teachers are involved with the selection process (Nath, 2008). This might indicate that private tutors might influence the selection process. Another interesting fact is that if the number of children increases, the probability of receiving stipend decreases.

In both cases (CBT girls and boys), the spouse's education plays a vital role in the selection. One possible explanation could be related to the universal female stipend program. These beneficiaries could be mothers of children exposed to the current program, and they realize how stipend can benefit their children. Thus they might communicate with the school and stipend committee and influence them to be selected as beneficiaries.

In contrast to the CBT, the World Bank had implemented its proxy means test quite well in the field. Table 10 reports that at least six variables can explain the selection process. For instance, it effectively targeted agricultural and non-agricultural labor-based households, excluding the remittance earners and households with solid walls (compared to no solid wall group). It also excluded households with more children and highly educated household heads. Moreover, targeting was correlated with one control variable which was not included in the guideline, such as the number of loans. However, the field implementation of the PMT method was quite well if compared to the guidelines of both models. The robustness check regressions also support the results with LPM (Table 13, 14, and 15 in Appendix).

6.2 Evaluating Targeting Efficiency

This section explores the household characteristics related to exclusion and inclusion error. Table 11 presents the factors influencing both implementation errors where the first three regression talks about the exclusion error and the last four regression are about the inclusion error by both CBT and PMT. At first, we reported the whole sample status of exclusion and inclusion errors to understand the general trend, and finally, all the specific program status as presented. We have not estimated the exclusion error for boys due to limited data (i.e., limited variation among 10% poor boys).

The regression results in columns 1 & 4 (table 11) present an overall understanding of implementation error and show that the spouse education again plays a significant role in reducing the likelihood of exclusion error, increasing the inclusion error. This result is also applicable for girls under the CBT method. Such a result might indicate that mother's education made them competent enough to bargain for their children's rights, making exclusion impossible. On the other hand, their smartness might enable them to lie about their economic status to the school or stipend selection committee and influence the erroneous inclusion.

Similarly, if there is a concrete road within the community, the chances of exclusion error reduce, and the probability of inclusion error increases both for the whole sample and in the CBT areas for girls. These results suggest that those who had good communication facilities had better chances to be selected. In general, the rich people live in those areas where there is good communication, and they might have frequent contact with school and stipend selection committee and get selected even if they are not poor. This finding established the results found by Khan (2014) and Schaeffing (2018).

Additionally, the probability of exclusion error by the CBT method decreases with the household head's agriculture labor work, tubewell ownership, and time to reach school, whereas it increases with the number of adults, amount of landholdings, and separate kitchen. On the other hand, the possibilities of inclusion error increase with land ownership of more than 1.5 acres (compared to less than 1.5 acres of land), having at least three cattle and time to travel to school and decreases with concrete roof, the concrete road in community motor pump holding, and share latrine. It might seem surprising that the time to travel to school reduces the exclusion error and increases inclusion error. The possible explanation is that those who live near the schools reach school by walking whereas others use public or own transport to reach school. As the schools are generally situated in the center of the town/village, those who live close to school might take more time than those who live in a distant place to reach school, and this closeness might influence the errors.

People might evaluate the poor in rural areas through their household characteristics, assets, and living condition. The above results suggest that the school selection committee does not follow the CBT guideline but uses their local perception of poverty to choose the beneficiary. This finding matches with the CBT selection (in table 8 and 9), where we saw how their poverty understanding and relationship influence the beneficiary selection.

In the PMT method, the chances of exclusion error increase with separate kitchen, cell phone, and asset value and decrease with household size, Agriculture Day laborer head, and the number of loans taken. In contrast, the inclusion error decreases with agri-laborer and has Tin/wood wall, increasing with total Agri-based asset value.

We checked the robustness of these results with the LPM and alternative poverty definition (such as a log of consumption expenditure and PMT score) and confirmed the relationship.

Table 11: Marginal Effect of Determining the Exclusion and Inclusion Error

VARIABLES	(1) Whole Sample Exclusion Error	(2) CBT Exclusion Error Girls	(3) PMT Exclusion Error	(4) Whole Sample Inclusion Error	(5) CBT Inclusion Error Girls	(6) CBT Inclusion Error Boys	(7) PMT Inclusion Error
	Dep. Var.: Poor not selected by the program Sample: Poor Households			Dep. Var.: Non-Poor Selected by the program Sample: Non-Poor Households			
Household Characteristics							
Head Education in Years	0.003 (0.006)	0.005 (0.008)	0.007 (0.006)	-0.002 (0.003)	-0.007 (0.005)	0.004 (0.003)	-9.63e-05 (0.006)
Spouse Education in Years	**-0.021*** (0.005)**	**-0.019** (0.008)**	**-0.024*** (0.006)**	**0.008*** (0.004)**	**0.012** (0.005)**	0.0003 (0.004)	0.009 (0.007)
Number of Infants	**-0.043* (0.025)**	-0.039 (0.032)	-0.024 (0.040)	**0.041** (0.016)**	0.043 (0.027)	-0.005 (0.021)	-0.001 (0.033)
Number of Adults	-0.020 (0.014)	**0.037* (0.021)**	**-0.052** (0.020)**	-0.006 (0.008)	-0.002 (0.014)	**-0.019** (0.009)**	0.012 (0.019)
Head Agriculture Day Laborer	**-0.125*** (0.031)**	**-0.152*** (0.055)**	**-0.117** (0.046)**	**-0.087* (0.046)**	-0.053 (0.089)	-0.017 (0.047)	**-0.159* (0.092)**
Living Standard							
Wall: Tin/CI/Wood	-0.034 (0.036)	-0.080 (0.056)	-0.048 (0.045)	-0.016 (0.033)	-0.019 (0.062)	0.032 (0.032)	**-0.148** (0.070)**
Wall: Brick	0.009 (0.040)	-0.001 (0.065)	-0.057 (0.053)	-0.0002 (0.035)	-0.069 (0.059)	0.011 (0.034)	0.017 (0.085)
Roof: Concrete	-0.004 (0.070)	-0.025 (0.146)	-0.021 (0.077)	**-0.068** (0.031)**	**-0.120** (0.056)**	-0.060 (0.040)	0.060 (0.074)
Separate Kitchen	0.070 (0.050)	-0.033 (0.086)	**0.133** (0.055)**	0.024 (0.051)	0.042 (0.082)	0.040 (0.060)	0.024 (0.104)
Share Latrine	0.037 (0.034)	**0.141** (0.059)**	-0.018 (0.044)	**-0.051** (0.025)**	**-0.114** (0.046)**	-0.030 (0.031)	-0.032 (0.056)
Owned Bicycle	-0.012 (0.029)	-0.082 (0.052)	0.035 (0.039)	-0.029 (0.022)	0.009 (0.036)	0.004 (0.025)	-0.022 (0.047)
Cellphone	**0.100** (0.049)**	0.071 (0.080)	**0.120** (0.050)**	-0.042 (0.036)	0.094 (0.079)	**-0.127*** (0.038)**	-0.025 (0.095)
Productive Assets							
Total Agri Land: Upto 1.5 Acres	0.016 (0.045)	0.020 (0.073)	0.066 (0.067)	0.034 (0.026)	**0.071* (0.041)**	-0.024 (0.034)	0.021 (0.055)
Total Agri Land: >1.5 Acres	-0.053 (0.073)	-0.034 (0.106)	-0.049 (0.135)	-0.031 (0.041)	-0.030 (0.065)	-0.051 (0.047)	0.088 (0.092)
Total Land	**0.001***(0.0002)**	**0.001***(0.0003)**	0.0004 (0.0004)	0.0001 (0.0001)	9.93e-05 (0.0001)	1.81e-05 (0.0001)	-0.0002 (0.0002)
Total Agri Asset Value	1.24e-06 (1.53e-06)	1.46e-07 (1.69e-06)	**1.14e-05** (4.47e-06)**	-3.14e-08 (2.20e-07)	-1.19e-06 (9.96e-07)	-1.23e-07 (2.44e-07)	**1.31e-06* (7.58e-07)**
Own Shallow Tube Well	-0.038 (0.038)	**-0.161** (0.067)**	-0.070 (0.058)	-0.0003 (0.040)	-0.017 (0.073)	0.031 (0.040)	0.050 (0.077)
Own Motor pump	-0.040 (0.053)	0.007 (0.158)	-0.086 (0.065)	**-0.078** (0.034)**	**-0.119** (0.051)**	-0.018 (0.047)	-0.115 (0.078)
Own at least 3 Cattles	0.013 (0.039)	-0.028 (0.053)	0.031 (0.047)	**0.053** (0.025)**	**0.119*** (0.043)**	0.006 (0.027)	0.055 (0.055)
Number of Loan Taken: 1 Loan	-0.037 (0.032)	-0.047 (0.056)	**-0.059* (0.032)**	0.012 (0.026)	0.023 (0.043)	0.023 (0.026)	-0.026 (0.078)
Number of Loan Taken: 2 Loans	-0.043 (0.040)	-0.051 (0.060)	**-0.057 (0.050)**	**0.048* (0.029)**	0.059 (0.044)	0.050 (0.034)	-0.033 (0.076)
Number of Loan Taken: 3&+ Loans	-0.070 (0.055)	-0.062 (0.081)	-0.127 (0.079)	0.013 (0.033)	0.009 (0.050)	0.026 (0.039)	0.016 (0.100)

At least 1 Agri loan	0.007 (0.040)	0.010 (0.062)	-0.030 (0.057)	0.011 (0.028)	0.009 (0.049)	-0.020 (0.031)	**0.126* (0.0732)**
Vulnerable Condition							
At least 1 Consumption loan	0.019 (0.047)	0.082 (0.068)	-0.005 (0.055)	0.006 (0.029)	-0.048 (0.052)	**0.060* (0.032)**	-0.078 (0.073)
No Food to Eat	0.032 (0.059)	-0.033 (0.084)	0.141 (0.088)	-0.035 (0.055)	-0.138 (0.110)	-0.006 (0.044)	0.155 (0.167)
Social Network							
Secondary School within Community	-0.011 (0.037)	-0.083 (0.070)	0.006 (0.044)	0.013 (0.025)	0.033 (0.040)	0.014 (0.027)	-0.026 (0.048)
Union Office within Community	0.045 (0.052)	-0.085 (0.086)	**0.112* (0.061)**	-0.029 (0.030)	-0.047 (0.048)	-0.014 (0.038)	0.024 (0.052)
Concrete Road within Community	**-0.056* (0.032)**	**-0.144*** (0.047)**	-0.022 (0.046)	**0.053** (0.024)**	**0.089** (0.038)**	0.011 (0.024)	0.009 (0.041)
Association Member	0.005 (0.032)	-0.019 (0.044)	0.071 (0.048)	-0.014 (0.021)	-0.052 (0.038)	0.022 (0.022)	-0.032 (0.044)
Student Specific Variable							
Students receive any private coaching	-0.020 (0.019)	0.003 (0.029)	-0.044 (0.027)	-0.012 (0.013)	-0.023 (0.024)	0.024 (0.016)	0.003 (0.0251)
Time to reach school	-1.17e-05 (0.0004)	**-0.004*** (0.001)**	0.0001 (0.0004)	4.45e-05 (0.0003)	**0.002*** (0.001)**	-0.0002 (0.0004)	**-0.002* (0.001)**
Divisional Fixed Effect	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Observations	797	299	428	1,583	647	630	306

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

7.0 Conclusions

This paper assessed the effectiveness of two poverty-based secondary school student targeting methods, namely CBT and PMT. Under the universal targeting method (1994-2008), the stipend program may not attract the poor students due to the stipend amount (less than $1) and their opportunity cost to work in a house or field (Mahmud, 2003). Then, in 2009, poverty-based targeting was introduced to include the excluded with the significant increase in stipend amount. The government of Bangladesh and the World Bank took different targeting mechanisms to select the poor beneficiary. However, the authorities need enough information to understand whether the program is implementing according to their expectation. Thus, this research sheds light on the gap between the policy guidelines and implantation, which might guide the authorities to rethink how they can proceed further and achieve the goal.

The study's findings are not satisfactory, and a good percentage of poor students are excluded from the program by both methods, whereas a significant number of non-poor students are benefiting from the program. Thus, the goal of the stipend program was not fulfilled, and a large amount of public money was not utilized appropriately.

We also found that although both methods were making significant mistakes in selecting poor students, the Proxy mean test (PMT) areas followed a good number of implementation guidelines. However, the rate of coverage was relatively low. Although it targeted up to 50^{th} percentile of poor students, this study found that only 19% of the poor students received the stipend. This is still an unsolved issue whether the presence of “Ghost Beneficiary.” According to Khan (2014), the schools kept two attendant registers for students. One was used for everyday school purposes and another for program officers. This might have relevance with the “Ghost Beneficiary” issue. However, this issue demands further research.

In addition, the exclusion error was relatively higher in PMT areas than the CBT method. Although the error distribution should have a higher number of errors near the threshold decile groups, both the inclusion and exclusion error spread among all the consumption decile groups. This might indicate poor targeting.

In contrast, the community-based method did not follow the guideline, but the stipend selection committee used their local knowledge of poverty to choose the beneficiaries. It is also evident that mother’s awareness about the stipend program and social network greatly influence the beneficiary selection process under the CBT method. The guideline-based regression and error-based regression support each other, where possible social networks such as living in a community with a good physical communication system (such as a concrete road) create a chance to meet the teacher and stipend selection committee may influence the to as these findings match with the qualitative studies of Khan (2014) and Schaeffing (2018).

Although the exclusion error is low compared to the PMT, the inclusion error was high in the CBT areas. Like PMT, the error distribution of the CBT's inclusion and exclusion error was almost equally distributed among all consumption decile groups, indicating the program's poor implementation.

Thus targeting Efficiency might be enhanced through proper monitoring by the program implementation authorities. In addition, we need to consider the local knowledge while implementing the community-based targeting method. Any uniform targeting policy might create inefficiency. Instead, we should clearly state the program's objective and let the community select how they will identify the poor. Afterward, the program authority should monitor whether they are implementing it correctly. In this way, we can reduce the gap between the policy guidelines and the implementation of community-based targeting.

On the other hand, apart from monitoring, the PTM guideline should be short so that the assessment takes less time, and those judgment criteria should be such that the potential beneficiaries cannot manipulate them. Then the proper implementation will enhance the performance of the program. Moreover, the authorities can develop a mixed method where firstly, they can take local poverty information and then build a PMT model for selection. This two-step procedure might adjust the errors of both targeting methods and enhance the Efficiency.

Finally, its time for the government and the World Bank to reevaluate their program’s implementation status, find the gap explored by this research, take the necessary steps to reduce these errors, and implement it according to the goal.

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Appendix

Table 12: PMT Weights (used for calculating PTM Score)

Variable	Weight
Division grouping: Khulna, Barisal, Rajshahi	0.088
Total agri land owned > 0 & <= 1.5 acres	0.044
Total agri land owned > 1.5 acres	0.127
Head Agriculture day laborer	-0.101
Head Non-Agriculture day laborer	-0.059
Non Head Agriculture day laborer in HH	-0.039
Non Head Non-Agriculture day laborer in HH	-0.063
Own at least three Cattles	-0.080
Wall-CI Sheet/Wood	-0.102
Wall-Mud Brick	-0.057
Wall-Hemp/hay/bamboo	-0.102
Roof-CI Sheet/wood	-0.189
Roof: Hemp/hay/bamboo	-0.203
Sanitary-Water Seal-Pacca Toilet	0.094
Permanent Kacha Toilet	0.041
Temp Kacha Toilet	0.016
Own Tubewell for Drinking Water	0.038
No electricity	-0.043
TV	0.143
Own Home Phone	0.248
Bicycle	0.072
Number of rooms in house is 2	0.116
Number of rooms in house is 3	0.180
Number of rooms in house is 4 or more	0.302
Children <15yrs in household=1	-0.100
Children<15yrs in household=2 or 3	-0.152
Children<15yrs in household=4 or more=	-0.220
Household size (2 members)	-0.147
Household size (3 members)	-0.267
Household size (4 members)	-0.364
Household size (5 members)	-0.450
Household size (6 members)	-0.522
Household size (7 members)	-0.563
Household size (8 members)	-0.595
Household size (9 and more members)	-0.634
Head education level - grade 5 to 9 completed	0.072
Head education level - SSC_HSC	0.167
Head education level - BA plus	0.192
Spouse education level - SSC_HSC	0.118
Spouse education level - BA plus	0.232
Remittance from Abroad	0.144
Distressed Household Head	-0.043
Constant	7.438

Source: World Bank 2013

Table 13: Robustness Check of CBT-Girls with Linear Probability Model

VARIABLES	(1) CBT Guideline	(2) CBT Guideline & GoB Poor	(3) CBT Guideline & Other Controls
CBT Guideline			
Land below 50 Decimal	-0.010 (0.025)	-0.017 (0.025)	-0.016 (0.029)
Yearly Income<30000	0.059 (0.053)	0.067 (0.054)	0.056 (0.067)
Vulnerable Group	0.026 (0.041)	0.033 (0.041)	0.009 (0.044)
Head Agri. Day Laborer	0.047 (0.052)	0.059 (0.052)	0.099* (0.050)
Head Non-Agri. Day Laborer	0.053 (0.047)	0.051 (0.047)	0.037 (0.046)
Non-Head Agri. Day Laborer in HH	0.063 (0.062)	0.067 (0.062)	0.055 (0.065)
Non-Head Non-Agri. Day Laborer in HH	-0.012 (0.041)	-0.012 (0.041)	0.004 (0.047)
At least 1 Shock in last 3 years	0.011 (0.025)	0.012 (0.025)	-0.015 (0.039)
Below 3rd Consumption Decile Threshold		-0.048 (0.030)	-0.042 (0.034)
Household Characteristics			
Head Education in Years			-0.004 (0.004)
Spouse Education in Years			0.015*** (0.005)
One Infant			0.005 (0.028)
Two Infants			0.135** (0.061)
Living Standard			
Owned Cellphone			0.013 (0.053)
Owned Bicycle			0.028 (0.029)
Solid Floor			-0.045 (0.033)
Share Latrine			-0.097*** (0.034)
Productive Assets			
Owned Pesticide Sprayer			0.046 (0.038)
Owned Motor Pump			-0.101** (0.043)
Vulnerable Condition			
At least 1 Health Shock after 2015			0.051 (0.041)
No Food to Eat			-0.044 (0.062)
Social Network			
Secondary School within the Community			0.064 (0.041)
Bazar within the Community			-0.0004 (0.032)
Union Office within the Community			-0.0004 (0.055)
Concrete Road within the Community			0.109*** (0.032)
Association Leader			-0.073 (0.049)
Student Specific Variable			
Students receive any private coaching			-0.012 (0.018)
Time to reach school			0.002*** (0.001)
Divisional Fixed Effect	Yes	Yes	Yes
Observations	1,372	1,372	1,054

Robust Standard Errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 14: Robustness Check of CBT-Boys with Linear Probability Model

VARIABLES	(1) CBT Guideline	(2) CBT Guideline & GoB Poor	(3) CBT Guideline & Other Controls
CBT Guideline			
Land below 50 Decimal	0.015 (0.018)	0.017 (0.018)	0.020 (0.024)
Yearly income<30000	0.010 (0.040)	0.011 (0.040)	-0.080** (0.036)
Vulnerable Group	0.092** (0.037)	0.091** (0.037)	0.078* (0.041)
Head Agri. Day Laborer	0.053 (0.046)	0.047 (0.048)	0.050 (0.048)
Head Non-Agri. Day Laborer	0.025 (0.038)	0.025 (0.038)	0.003 (0.038)
Non-Head Agri. Day Laborer in HH	0.004 (0.062)	0.002 (0.061)	0.028 (0.060)
Non-Head Non-Agri. Day Laborer in HH	-0.019 (0.034)	-0.020 (0.034)	0.012 (0.039)
At least 1 shock after 2015	0.003 (0.019)	0.003 (0.019)	-0.014 (0.036)
Below 1st Consumption Decile Threshold		0.040 (0.046)	0.037 (0.048)
Household Characteristics			
Head Education in Years			0.003 (0.006)
Spouse Education in Years			0.007 (0.004)
1 Children			-0.024 (0.022)
2 Children			-0.015 (0.028)
3&+ Children			-0.075* (0.040)
Living Standard			
Cellphone			-0.088 (0.054)
Owned Bicycle			0.019 (0.025)
At least 1 Consumption Loan			0.065 (0.043)
Solid Floor			-0.003 (0.024)
Share Latrine			-0.0005 (0.032)
Productive Assets			
Owned Pesticide Sprayer			0.021 (0.029)
Own Motor Pump			-0.019 (0.036)
At least 1 Agri Loan			0.033 (0.034)
Vulnerable Condition			
No Food to Eat			0.057 (0.053)
At least 1 health shock after 2015			-0.005 (0.037)
Social Network			
Secondary School within Community			0.005 (0.031)
Bazar within Community			-0.008 (0.028)
Union Office within Community			-0.028 (0.038)
Concrete Road within Community			-0.008 (0.024)
Association Leader			0.004 (0.043)
Student Specific Variable			
Students receive any private coaching			0.031** (0.014)
Time to reach school			-0.0002 (0.0004)
Divisional Fixed Effect	Yes	Yes	Yes
Observations	994	994	784

Robust Standard Errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 15: Robustness Check of PMT with Linear Probability Model

VARIABLES	(1) PMT Guideline	(2) PMT Guideline & PMT Poor	(3) PMT Guideline & Other Controls
PMT Guideline			
Total Agri Land: Upto 1.5 Acres	0.030 (0.033)	0.030 (0.034)	0.028 (0.036)
Total Agri Land: More than 1.5 Acres	0.050 (0.045)	0.050 (0.046)	0.043 (0.053)
Head Agriculture Day Laborer	0.067 (0.042)	0.067 (0.043)	0.059 (0.044)
Head Non-Agri. Day Laborer	0.131* (0.070)	0.132* (0.071)	0.144* (0.075)
Non-Head Agri. Day Laborer in HH	-0.019 (0.048)	-0.019 (0.049)	-0.011 (0.048)
Non-Head Non-Agri. Day Laborer in HH	-0.074 (0.050)	-0.074 (0.050)	-0.083 (0.050)
Own at least 3 Cattles	0.018 (0.041)	0.018 (0.041)	0.018 (0.041)
Solid Wall: Tin/CI/Wood	-0.084** (0.041)	-0.084** (0.041)	-0.082** (0.040)
Solid Wall: Mud	-0.037 (0.046)	-0.037 (0.046)	-0.048 (0.046)
Wall: Bamboo/straw/leaf	-0.025 (0.064)	-0.025 (0.064)	-0.003 (0.060)
Concrete Roof	0.034 (0.048)	0.034 (0.048)	0.017 (0.048)
Own Tube Well	0.016 (0.030)	0.016 (0.030)	0.009 (0.030)
No Electricity Connection	-0.032 (0.045)	-0.032 (0.045)	-0.036 (0.043)
Owned TV	-0.002 (0.036)	-0.002 (0.036)	-0.014 (0.037)
Owned Bicycle	-0.044 (0.037)	-0.044 (0.037)	-0.043 (0.038)
Number of Rooms: 2-3	-0.021 (0.042)	-0.021 (0.043)	-0.024 (0.044)
Number of Rooms: 4&+	0.211 (0.174)	0.211 (0.174)	0.202 (0.178)
Number of Children: 2/3 Childs	-0.063* (0.035)	-0.063* (0.035)	-0.061* (0.036)
Number of Children: 4&+ Childs	-0.037 (0.042)	-0.037 (0.042)	-0.048 (0.043)
Number of total households	0.017* (0.010)	0.017* (0.010)	0.015 (0.010)
Head Education Level: 5-9 Years	-0.019 (0.037)	-0.019 (0.037)	-0.021 (0.038)
Head Education Level: 10-12 Years	0.027 (0.054)	0.027 (0.055)	0.035 (0.055)
Head Education Level:12+ Years	-0.159*** (0.052)	-0.159*** (0.052)	-0.159*** (0.050)
Head Education Level: 10&+ Years	-0.001 (0.062)	-0.001 (0.062)	-0.001 (0.059)
Remittance from Abroad	-0.105 (0.064)	-0.105 (0.064)	-0.090 (0.061)
Below 5th Consumption Decile Threshold		-8.28e-05 (0.031)	0.001 (0.033)
Productive Assets			
Own Weeding Tool			0.040 (0.030)
Own shallow Tube well			-0.046 (0.046)
Number of Loan Taken:1 Loan			0.040 (0.039)
Number of Loan Taken: 2 Loans			0.033 (0.047)
Number of Loan Taken: 3&+ Loans			0.129** (0.061)
Vulnerable Condition			
No Food to Eat			-0.082 (0.066)
Social Network			
Secondary School within Community			-0.017 (0.039)
Bazar within Community			0.047 (0.034)
Union Office within Community			-0.068 (0.044)
Concrete Road within Community			0.017 (0.030)
Association Member			-0.041 (0.031)
Divisional Fixed Effect	Yes	Yes	Yes
Observations	796	796	796

Robust Standard Errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 16: Robustness Check of Exclusion and Inclusion Error with Linear Probability Model

VARIABLES	(1) Whole Sample Exclusion Error	(2) CBT Exclusion Error Girls	(3) PMT Exclusion Error	(4) Whole Sample Inclusion Error	(5) CBT Inclusion Error Girls	(6) CBT Inclusion Error Boys	(7) PMT Inclusion Error
	Dep. Var.: Poor not selected by the program Sample: Poor Households			Dep. Var.: Non-Poor Selected by the program Sample: Non-Poor Households			
Household Characteristics							
Head Education in Years	0.003 (0.006)	-0.001(0.010)	0.00740 (0.007)	-0.002 (0.003)	-0.008 (0.005)	0.004 (0.003)	-0.0005 (0.007)
Spouse Education in Years	-0.022*** (0.006)	-0.015 (0.009)	-0.028*** (0.007)	0.009** (0.003)	0.012** (0.006)	0.001 (0.004)	0.009 (0.008)
Number of Infants	-0.042 (0.029)	-0.047 (0.038)	0.00121 (0.042)	0.046** (0.019)	0.049 (0.030)	-0.001 (0.022)	-0.001 (0.034)
Number of Adults	-0.016 (0.014)	0.026 (0.022)	-0.0358 (0.022)	-0.005 (0.008)	-0.005 (0.015)	-0.017* (0.009)	0.017 (0.022)
Head Agriculture Day Laborer	-0.138***(0.039)	-0.165** (0.074)	-0.135** (0.058)	-0.074** (0.032)	-0.049 (0.078)	-0.014 (0.050)	-0.097* (0.056)
Living Standard							
Wall: Tin/CI/Wood	-0.038 (0.037)	-0.088 (0.064)	-0.045 (0.053)	-0.021 (0.032)	-0.020 (0.063)	0.028 (0.036)	-0.153** (0.068)
Wall: Brick	0.007 (0.043)	-0.034 (0.080)	-0.032 (0.061)	-0.0003 (0.034)	-0.070 (0.061)	0.010 (0.038)	0.013 (0.081)
Roof: Concrete	0.005 (0.071)	-0.049 (0.187)	0.010 (0.085)	-0.070* (0.038)	-0.120* (0.068)	-0.065 (0.053)	0.070 (0.086)
Separate Kitchen	0.087 (0.067)	-0.026 (0.090)	0.177** (0.078)	0.016 (0.046)	0.036 (0.075)	0.045 (0.056)	0.018 (0.133)
Share Latrine	0.037 (0.034)	0.120* (0.061)	-0.011 (0.048)	-0.050** (0.023)	-0.111** (0.044)	-0.025 (0.033)	-0.012 (0.055)
Owned Bicycle	-0.006 (0.032)	-0.059 (0.063)	0.033 (0.047)	-0.029 (0.023)	0.001 (0.037)	0.004 (0.028)	-0.039 (0.056)
Cellphone	0.099* (0.055)	0.035 (0.095)	0.169** (0.069)	-0.038 (0.037)	0.076 (0.062)	-0.150** (0.064)	-0.056 (0.113)
Productive Assets							
Total Agri Land: Upto 1.5 Acres	0.027 (0.053)	0.019 (0.100)	0.083 (0.065)	0.034 (0.027)	0.080* (0.044)	-0.019 (0.036)	0.020 (0.060)
Total Agri Land: >1.5 Acres	-0.007 (0.067)	-0.040 (0.126)	0.003 (0.087)	-0.032 (0.052)	-0.023 (0.072)	-0.048 (0.050)	0.098 (0.097)
Total Land	0.0003*** (9.80e05)	0.0005* (0.0002)	0.0002* (0.0001)	0.0001 (0.0001)	9.02e-05 (0.000150)	1.16e-05 (0.0001)	-0.0002 (0.0002)
Total Agri Asset Value	2.59e-07** (1.24e-07)	2.65e-07 (1.95e-06)	2.38e-07 (1.57e-07)	-2.25e-09 (1.75e-07)	-2.21e-07 (1.70e-07)	-7.15e-08 (1.09e-07)	1.92e-06* (1.04e-06)
Own Shallow Tube Well	-0.020 (0.040)	-0.151 (0.099)	0.018 (0.052)	-0.001 (0.042)	-0.032 (0.073)	0.023 (0.048)	0.0347 (0.097)
Own Motor pump	-0.023 (0.057)	0.031 (0.209)	-0.008 (0.079)	-0.076** (0.030)	-0.111** (0.048)	-0.017 (0.043)	-0.127 (0.092)
Own at least 3 Cattles	0.019 (0.040)	-0.019 (0.061)	0.033 (0.054)	0.054* (0.028)	0.122** (0.050)	0.011 (0.029)	0.0792 (0.073)
Number of Loan Taken: 1 Loan	-0.045 (0.034)	-0.043 (0.068)	-0.047 (0.041)	0.010 (0.027)	0.018 (0.047)	0.018 (0.027)	-0.0283 (0.082)
Number of Loan Taken: 2 Loans	-0.045 (0.041)	-0.045 (0.071)	-0.048 (0.058)	0.048 (0.030)	0.057 (0.047)	0.042 (0.038)	-0.0313 (0.080)
Number of Loan Taken: 3&+ Loans	-0.084 (0.059)	-0.071 (0.090)	-0.136 (0.090)	0.008 (0.035)	-0.001 (0.056)	0.018 (0.043)	0.0125 (0.107)

At least 1 Agri loan	0.024 (0.042)	0.024 (0.070)	0.004 (0.064)	0.005 (0.029)	-0.003 (0.053)	-0.021 (0.032)	0.165* (0.095)
Vulnerable Condition							
At least 1 Consumption loan	0.032 (0.052)	0.065 (0.083)	0.026 (0.070)	0.004 (0.029)	-0.038 (0.050)	0.075 (0.049)	-0.092 (0.074)
No Food to Eat	0.031 (0.063)	-0.032 (0.097)	0.117 (0.079)	-0.023 (0.043)	-0.094 (0.077)	-2.21e-05 (0.051)	0.089 (0.256)
Social Network							
Secondary School within Community	-0.015 (0.039)	-0.095 (0.086)	-0.010 (0.039)	0.016 (0.027)	0.054 (0.046)	0.014 (0.033)	-0.016 (0.048)
Union Office within Community	0.044 (0.060)	-0.103 (0.120)	0.131** (0.062)	-0.034 (0.032)	-0.057 (0.053)	-0.016 (0.042)	0.014 (0.055)
Concrete Road within Community	-0.051 (0.033)	-0.130** (0.055)	-0.010 (0.048)	0.053** (0.024)	0.090** (0.040)	0.013 (0.025)	0.010 (0.048)
Association Member	0.003 (0.032)	-0.021 (0.053)	0.061 (0.046)	-0.009 (0.021)	-0.035 (0.037)	0.024 (0.026)	-0.023 (0.049)
Student Specific Variable							
Students receive any private coaching	-0.016 (0.020)	-0.001 (0.032)	-0.032 (0.027)	-0.015 (0.013)	-0.022 (0.024)	0.020 (0.016)	-0.012 (0.029)
Time to reach school	-4.04e-05 (0.001)	-0.003* (0.002)	0.0003 (0.001)	1.01e-05 (0.0003)	0.002*** (0.001)	-0.0001 (0.0003)	-0.0009** (0.0004)
Divisional Fixed Effect	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Observations	797	299	428	1,583	647	630	306

Robust Standard Errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 17: Robustness Check of Exclusion and Inclusion Error with Log Consumption Expenditure and PMT Score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Whole Sample Exclusion Error	CBT Exclusion Error Girls	PMT Exclusion Error	Whole Sample Inclusion Error	CBT Inclusion Error Girls	CBT Inclusion Error Boys	PMT Inclusion Error
	Dep. Var.: Poor not selected by the program Sample: Poor Households			Dep. Var.: Non-Poor Selected by the program Sample: Non-Poor Households			
Household Characteristics							
Head Education in Years	0.002 (0.006)	0.004 (0.008)	0.006 (0.007)	-0.002 (0.003)	-0.006 (0.005)	0.005 (0.003)	-0.0003 (0.006)
Spouse Education in Years	-0.022*** (0.005)	-0.019** (0.008)	-0.025*** (0.007)	0.008*** (0.003)	0.013** (0.005)	0.002 (0.003)	0.009 (0.007)
Number of Infants	-0.028 (0.025)	-0.023 (0.034)	-0.005 (0.039)	0.038** (0.016)	0.038 (0.027)	-0.012 (0.022)	0.005 (0.035)
Number of Adults	-0.013 (0.015)	0.045** (0.021)	-0.042** (0.021)	-0.007 (0.009)	-0.005 (0.014)	-0.021** (0.009)	0.012 (0.020)
Head Agriculture Day Laborer	-0.108*** (0.034)	-0.130** (0.062)	-0.094* (0.051)	-0.089* (0.047)	-0.063 (0.088)	-0.024 (0.049)	-0.155 (0.098)
Living Standard							
Wall: Tin/CI/Wood	-0.026 (0.036)	-0.066 (0.058)	-0.039 (0.046)	-0.016 (0.032)	-0.021 (0.062)	0.029 (0.031)	-0.147** (0.068)
Wall: Brick	-0.001 (0.042)	-0.005 (0.066)	-0.076 (0.055)	0.002 (0.036)	-0.063 (0.059)	0.016 (0.036)	0.025(0.087)
Roof: Concrete	0.039 (0.074)	0.019 (0.149)	0.033 (0.080)	-0.073** (0.035)	-0.133** (0.062)	-0.074 (0.046)	0.073 (0.084)
Separate Kitchen	0.062 (0.051)	-0.031 (0.088)	0.112** (0.053)	0.026 (0.051)	0.042 (0.082)	0.048 (0.057)	0.014 (0.106)
Share Latrine	0.040 (0.034)	0.138** (0.059)	-0.019 (0.045)	-0.053** (0.025)	-0.117** (0.046)	-0.031 (0.031)	-0.036 (0.055)
Owned Bicycle	-0.030 (0.031)	-0.106** (0.053)	0.020 (0.039)	-0.026 (0.023)	0.014 (0.037)	0.011 (0.026)	-0.031 (0.049)
Cellphone	0.096** (0.048)	0.055 (0.079)	0.122** (0.048)	-0.044 (0.036)	0.091 (0.079)	-0.125*** (0.037)	-0.020 (0.095)
Productive Assets							
Total Agri Land: Upto 1.5 Acres	-0.007 (0.043)	-0.009 (0.067)	0.055 (0.068)	0.038 (0.025)	0.074* (0.042)	-0.023 (0.034)	0.010 (0.053)
Total Agri Land: >1.5 Acres	-0.097 (0.073)	-0.096 (0.103)	-0.070 (0.136)	-0.025 (0.042)	-0.021 (0.066)	-0.046 (0.050)	0.075 (0.086)
Total Land	0.001*** (0.0002)	0.001*** (0.0002)	0.0003 (0.0003)	0.0001 (0.0001)	0.0001 (0.0001)	2.85e-05 (0.0001)	-0.0002 (0.0002)
Total Agri Asset Value	1.17e-06 (1.43e-06)	7.95e-08 (1.66e-06)	1.07e-05** (4.33e-06)	-3.32e-08 (2.24e-07)	-1.25e-06 (1.03e-06)	-1.34e-07 (2.51e-07)	1.25e-06* (7.58e-07)
Own Shallow Tube Well	-0.047 (0.038)	-0.176** (0.069)	-0.081 (0.057)	0.002 (0.040)	-0.012 (0.074)	0.036 (0.041)	0.048 (0.077)
Own Motor pump	-0.047 (0.050)	-0.013 (0.156)	-0.080 (0.063)	-0.078** (0.034)	-0.116** (0.052)	-0.009 (0.047)	-0.109 (0.076)
Own at least 3 Cattles	-0.006 (0.040)	-0.046 (0.056)	0.014 (0.048)	0.058** (0.027)	0.125*** (0.043)	0.009 (0.030)	0.042 (0.059)
Number of Loan Taken: 1 Loan	-0.041 (0.032)	-0.05211 (0.057)	-0.059* (0.032)	0.012 (0.026)	0.023 (0.043)	0.021 (0.026)	-0.020 (0.080)
Number of Loan Taken: 2 Loans	-0.049 (0.041)	-0.051 (0.060)	-0.063 (0.051)	0.048* (0.029)	0.060 (0.044)	0.052 (0.035)	-0.0367 (0.074)
Number of Loan Taken: 3&+ Loans	-0.057 (0.053)	-0.032 (0.082)	-0.123 (0.078)	0.013 (0.033)	0.008 (0.051)	0.021 (0.038)	0.020 (0.100)

At least 1 Agri loan	0.009 (0.039)	0.014 (0.061)	-0.030 (0.055)	0.011 (0.028)	0.009 (0.049)	-0.023 (0.031)	0.125* (0.074)
Vulnerable Condition							
At least 1 Consumption loan	0.030 (0.047)	0.081 (0.067)	0.010 (0.055)	0.007 (0.029)	-0.047 (0.052)	0.060* (0.032)	-0.079 (0.073)
No Food to Eat	0.030 (0.059)	-0.035 (0.083)	0.159* (0.084)	-0.034 (0.055)	-0.138 (0.110)	-0.014 (0.045)	0.147 (0.169)
Social Network							
Secondary School within Community	-0.019 (0.037)	-0.078 (0.072)	-0.006 (0.044)	0.013 (0.025)	0.033 (0.040)	0.016 (0.027)	-0.027 (0.047)
Union Office within Community	0.053 (0.051)	-0.083 (0.085)	0.124** (0.057)	-0.030 (0.029)	-0.047 (0.048)	-0.008 (0.038)	0.009 (0.057)
Concrete Road within Community	-0.057* (0.032)	-0.142*** (0.047)	-0.018 (0.045)	0.052** (0.024)	0.090** (0.038)	0.010 (0.023)	0.005 (0.041)
Association Member	0.005 (0.032)	-0.023 (0.043)	0.074 (0.050)	-0.014 (0.021)	-0.052 (0.038)	0.023 (0.022)	-0.027 (0.046)
Student Specific Variable							
Students receive any private coaching	-0.019 (0.019)	0.007 (0.029)	-0.040 (0.026)	-0.012 (0.013)	-0.025 (0.024)	0.023 (0.016)	0.002 (0.026)
Time to reach school	-0.0001(0.0004)	-0.004*** (0.001)	-1.41e-05 (0.0004)	5.32e-05 (0.0003)	0.002*** (0.001)	-0.0002 (0.0004)	-0.002** (0.001)
Log Consumption Expenditure and PMT Score							
Log Consumption Expenditure	-0.081 (0.055)	-0.143 (0.118)	-0.053 (0.066)	0.019 (0.027)	0.001 (0.050)	-0.023 (0.031)	-0.085 (0.075)
PMT Score	0.002* (0.001)	0.002 (0.002)	0.003* (0.002)	-0.0003 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.001 (0.001)
Divisional Fixed Effect	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Observations	797	299	428	1,583	647	630	306

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1