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Research Article

Impact of Cash Transfers on School Enrolment and Attendance by Gender in Kenya

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Abstract

School enrolment and attendance are education performance outcomes that are important for human capital development. In Kenya and other developing countries, majority of children have low school enrolment and attendance ratios due to low access to social services by poor families and gender differences. This paper investigates the impact of cash transfers on human capital development through school enrolment and attendance in Kenya. We applied nonlinear and propensity score matching regression models on a nationally representative household survey to investigate the impact of non-conditional government cash transfers on children's school enrolment and attendance. The empirical evidence shows that children in cash transfer-receiving households differ from those in non-recipient households. We note that the gender gap in school enrolment and attendance is narrowing but girls are still in a disadvantaged position. We find that cash transfers have an impact on human capital development through children's school enrolment and attendance in Kenya and they are capable of addressing gender disparities with significant effects in both girls and boys, though the girls are still in a disadvantaged position. To effectively disrupt the intergenerational cycle of poverty, the building of sufficient human capital through cash transfers requires enhancement of the fiscal space and establishment of governance administrative structures that are accountable and transparent in their delivery mechanism of cash transfers. To bridge the gender gap, gender mainstreaming should take centre stage in the allocation of cash transfers.

Keywords

Gender, Enrolment, Attendance, Cash Transfers, Human Capital Development

1. Introduction

Education has been identified as a human capital investment that is an engine for economic growth and development [38-42] emphasizes the critical role human capital (education) plays in economic growth. Pace *et a*l. regards education as an economic good that's consumable for its utility, as a capital good and an input in economic development and social transformation [43]. Barro and Lee find schooling to be positively associated with the growth rate of per capita GDP [44]. Schultz suggests that higher initial levels of education are linked with subsequent rapid economic growth [39] while [40] find a causal relationship between human capital and economic growth. Schultz shows that advanced schooling increased private wage returns [38].

In Kenya and over the years, girls lag boys in education access and performance in both primary and secondary schools [18, 19]. The Net Enrolment Rate for girls in primary stood at 89.9 percent in 2015/16 compared to that of boys at 92.2 percent. In secondary enrolment, girls lagged boys mar-

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ginally by 0.4 percentage points in 2015/16. Kenya National Bureau of Statistics (KNBS) shows that, except at the primary level, females had enrolment rates lower than males at different levels of schooling [18, 19]. Literacy levels for females were lower at 80.2 percent in 2015/16 compared to 89.0 percent for males [19]. These disparities have affected attainment of requisite human capital development for females.

To invest in human capital and address gender disparities, governments all over the world have developed Cash Transfer (CT) programmes to be the cornerstone in the investment of human capital in children from vulnerable families. CT programmes have demonstrated that poor families can invest in their children through education as CTs form a source of paying school fees and out of pocket expenditures. The CTs enable poor families to surmount the challenges of accessibility and affordability to educational services thus resulting in increased school enrolment and attendance. Grounded on international best practices and lessons learned especially from some African, Latin American and Asian countries on the impact of CTs on poor housholds, the Government of Kenya in collaboration with her development partners established CT programmes that transfer financial support directly to vulnerable households to cushion them against income shocks in order to meet their basic consumption requirements [33, 30, 23].

The four CT programmes under the National Safety Net Programme [33, 30, 23] are: Cash Transfer to Orphans and Vulnerable Children (CT-OVC), launched in 2004 to cater for the needs of children orphaned and made vulnerable by HIV/AIDS and poverty; Persons with Severe Disabilities Cash Transfer (PWSD-CT) to enhance the capacities of care givers and improvement of the livelihoods of PWSD; and Older Persons Cash Transfer to offer regular and predictable CTs to poor and vulnerable persons aged 65 years and above in needy households; the Hunger Safety Net Programme (HSNP) to cushion poor families and vulnerable households against hunger in arid areas. The CT programmes implemented by the Government of Kenya have similar objectives of improving the livelihoods of households; cushioning households against shocks to reduce poverty; promoting household food consumption and food security; and promoting human capital development in children through an increase in schooling of children aged 6-17 years, and reducing under-five mortality and morbidity through increased uptake of health care especially in immunization, growth monitoring and vitamin-A supplementation.

Cash transfer programmes have been linked to improvements in human capital investments and outcomes. At the international level, CTs have been linked to enhanced school enrolment and attendance [54, 17]; improved maternal and child health care use and outcomes including antenatal visits, delivery at a health facility, skilled attendance at birth, and vaccination for mothers and reduced incidences of low birthweight in children [14]; reduction in mortality in children under five and women [35]; consumption smoothing and expenditure sustainability [5]; good health and nutrition [25]; and overall societal well-being [27, 63]. In Kenya, CT programmes are associated with reduction in incidences of diarrhoea [78], improved mental health [16], delay in sexual encounter [8], decrease in early pregnancies [9], increased labour supply [66], increased spending on health and food [50], and enhanced school enrolment and attendance [49].

2. Justification of the Study

This study contributes empirical evidence on issues that have been fronted at the international level to mitigate gender inequality to address the challenge of poverty. The Sustainable Development Goals (SDGs) underscore the policies that have been formulated to address the problems of gender inequality and poverty facing women and girls. The Republic of Kenya emphasizes on investment in the people through the provision of education and health care to build quality human capital to spur economic growth, reduce poverty, and address gender differences [29]. In as much as the Government of Kenya has pronounced itself on building human capital that is gender neutral, gender gaps in school enrolment and access to health care remain [32]. Gender disparities have been considered in the existing literature [53] as one of the factors that undermine the realization of poverty reduction strategies.

Developing countries are increasingly using CTs with the aim of reducing poverty and supporting investments in child human capital. CTs programmes have therefore, become an important component of poverty reduction strategies and social protection in the developing world [62]. To cushion poor families against shocks and reduce poverty, governments all over the world have developed social protection mechanisms to deal with social risks, mitigate shock induced poverty, and diminish economic vulnerability. These interventions support poor households to meet their basic needs, improve livelihoods, and invest in human capital development (HCD). Cruz and Ziegelhofer term CTs as a principal contributor to child HCD through its impact on child education, nutrition, and health [60]. Therefore, CTs can reduce poverty in the short run while the recipient households should in the long run invest in HCD in order to break intergenerational poverty transmissions. Existing literature [47, 12] have documented the impacts of the pioneer social protection in the world, PROGRESA/Oportunidades, on the poor. There is scarcity of literature on the impact of CTs on child enrolment and attendance by gender in Kenya. Moreover, it is not clear whether CTs have differentiated impact on school enrolment and attendance for boys and girls.

The paper provides evidence on the potential impact of the Government of Kenya unconditional CT programmes on school education performance outcomes; enrolment and attendance differentiated by gender. The policy implication of the analyses will break the intergenerational cycle of poverty, improve gender differences, enhance asset endowments, improve employability and lead to changes in household and individual behaviours through productive investment and labour allocation. The objective of this paper, therefore, is to determine whether there are gender differences on children school enrolment and attendance and estimate the impact of CTs on children school enrolment and attendance for boys and girls in Kenya, as a core of HCD.

3. Literature Review

The human capital theory (HCT) was developed by [45, 70]. The theory was elevated into economic modelling with the publication of *Investment in Human Beings supplement volume by the Journal of Political Economy* in 1962. The human capital theory seeks to support investment in education to increase the productivity and efficiency of labour [43]. The theory underpins the importance of investment in education in the production process of goods and services [43]. In the HCT, education is assumed to increase the marginal product of labour and thereafter the wage rate as per the equilibrium of the firm's employment [70]. The theoretical framework on how households make decisions was developed by [69, 51]. Two types of household decision-making models that are classified as unitary and non-unitary have been used to investigate decisions on child schooling.

The theoretical literature assumes that CTs confers both a price and an income effect to the recipient households. According to [26], the CTs cause a price effect due to a reduction in shadow wages of children occupying their time in activities other than schooling while an income effect is due to the CTs increasing the household total income.

The reviewed empirical literature supports the primacy of CTs to address gender differences in access to school attendance and enrolment. Cash transfers are a social protection mechanism that builds human capital and reduces the poorest households' susceptibility against shocks through consumption smoothing and expenditure sustainability [5]. A strong relationship has been found between CTs and school enrolment among children of secondary school-going age but not on school attendance [54] while [17] find the programme to improve enrolment rates and decreased dropout rates in Malawi.

De Groot *et al.* find impacts and differences across gender in secondary schooling that are significantly skewed towards enrolment for boys [3]. Baez and Camacho show that children in the treatment group are more likely than children in the control group to finish high school, especially girls and recipients in rural areas [2]. Evans *et al.* supports this assertion by showing improvements in primary school attendance and completion especially for girls [4]. Hagen-Zanker *et al.* and Benhassine *et al.* dispute the issue of CTs benefiting girls more than boys but contend that CTs increase school attendance for both without noticeable gender differences [6, 57]. Schultz show that orphaned children, poverty, gender, and rural residence significantly contributed to educational disparities between children of school-going age [34]. Other studies [13] find increase in child labour to adversely affect school attendance.

Empirical results [28] find safety nets to impact future generations, through enhancing education and health outcomes of children in extremely poor households. Positive impacts have been found on schooling that are robust with time, and reductions in work for school going children [56]. Sebastian *et al.* find programme to be more advantageous to secondary school-aged girls' enrolment than boys' enrolment [46]. Handa and Park find CTs to impact secondary school enrolment and attendance for girls [7]. Attanasio *et al.* find programme effects to significantly increase school participation and enrolment rates and reduced domestic work participation for children in both rural and urban areas [65]. Miller and Tsoka find children in the treatment of a CT in poor households to have a positive effect in children school enrolment and attendance with accompanied higher education expenditures, and a decrease in labour participation [22].

Analysis from the Kenya CT-OVC programme show a reduced likelihood of pregnancy through improvement of enrolment of young women in school, financial stability of the household, and delayed age at first sex [9]. Ward *et al*. find increased real household consumption levels leading to a reduction in poverty levels, increased enrolment, or attendance in basic schooling with significant impact for boys and poorer households [1]. Huebler finds poverty to be detrimental to school attendance [13]. The Kenya CT-OVC Evaluation Team find substantial impact on secondary school enrolment [49]. These findings are contradicted by [24, 68] who find no significant impact of the HSNP on education attendance and enrolment rates. Merttens *et al.* find similar results on the impact of CTs in the second phase of HSNP [21]. This contradiction may be explained by the fact that access and cost may not be the key barriers to schooling in Kenya and the HSNP is specific to hunger safety nets.

4. Methodological Framework

This study argues that CTs to poor households may be used to invest in human capital formation. Transmission channels of transfers to households are outlined by [64]. The channels assume that through capital accumulation and enhancement, CTs improve HCD, productivity and employability that will lead to poverty reduction. In this case, the CTs enter the household demand function to improve child HCD through an income effect that enables the households to afford quality educational outcomes through school enrolment and attendance for the children.

The potential mechanisms through which CTs impact recipient's decision making on household expenditures include change in household preferences on investments in child schooling and relaxation of the household budget constraint, which allows the household to change its expenditure composition. The mechanism also assumes that parents are altruistic toward investments in children's HCD as they make intertemporal decisions about the future of their children. It is expected that the capital accumulation will bring the household out of poverty and help to minimize intergenerational poverty transmission.

4.1. Theoretical Model

The HCT model applicable in this paper was developed by [45, 70]. The theory underpins the importance of investment in education and training in the production process of goods and services [43, 48]. The HCT postulates that investment in education and training increases the productivity and efficiency of labour [43]. Investment in HCD can be classified into; pre-school, basic and higher schooling, post-school training, health, migration, information, and investment in the production of children or investment of bearing children [37].

Becker developed the HCT for schooling from the concept of a student being in school and may work or may not work [70]. The student earnings vary throughout the period in school and out of school. The student faces direct costs to meet his/her investment in schooling. The net earnings of the student is the difference between his/her real earnings and direct school costs represented in function (1).

$$W = MP - \kappa \tag{1}$$

Where W is the net earnings, MP represents marginal product assumed to be equal to actual earnings and κ is direct school costs. Function (1) can be re-written to include MP_0, which is the marginal product that could have been received.

$$W = MP_0 - (MP_0 - MP + \kappa) = MP_0 - C \tag{2}$$

Where C represents the total amount of direct and indirect school costs. [70] argues that a school should be treated as a special form of firm where students are a special type of trainees to allow the application of the investment in HCT that is applied on the job training. We, therefore, turn to the theory of the firm behaviour in enhancing the workers' productivity through training and learning of new skills. A firm is in equilibrium if it maximizes its profits, and its marginal product is equal to wages as shown in function (3).

$$MP_t = W_t \tag{3}$$

Where MP_t is the marginal product in time t and W_t are wages paid to workers in time t. Conditions in function (3) will change if the firm invests in the training of its workers as the current expenditures will be higher than future expenditures. The net present value of the firm's receipts and expenditures is represented by function (4).

$$\sum_{t=0}^{n-1} \frac{R_t}{(1+i)^{t+1}} = \sum_{t=0}^{n-1} \frac{E_t}{(1+i)^{t+1}} \tag{4}$$

Where R_t is the firm's receipts in period t, E_t is the firm's expenditure in period t, i is the discount rate, and n represents the operational periods for the firm.

Function (4) changes into function (5) when factoring in the period of training where expenditures equal wages combined with the cost of training during that period. In subsequent periods, expenditures and wages are equal hence receipts would equal marginal product in all other periods.

$$MP_0 + \sum_{t=0}^{n-1} \frac{MP_t}{(1+i)^{t+1}} = W_0 + \kappa + \sum_{t=0}^{n-1} \frac{W_t}{(1+i)^{t+1}} \tag{5}$$

Function (5) can be reduced to function (6) by letting $G = \sum_{t=0}^{n-1} \frac{MP_t - W_t}{(1+i)^{t+1}}$, which is the increase in receipts in the future over future outlays.

$$MP_0 + G = W_0 + \kappa + G \tag{6}$$

The opportunity cost of training can be estimated by function (7) by incorporating the total cost, C, into the training component that arises as a result of the time spent by the employee in training and not for producing the current output and the training outlays, κ.

$$MP_0' + G = W_0 + C \tag{7}$$

Where MP_0' is what the firm could have produced if the firm did not have any expenditure on training.

Letting wages, W_t be equal to marginal products for all t=1,…, n-1, and letting G=0, then function (7) is reduced to function (8) for the actual marginal product.

$$MP_0 = W_0 + \kappa \tag{8}$$

In a competitive market, the equilibrium of a firm giving training for its employees can be represented in function (9).

$$MP_0 + \sum_{t=0}^{n-1} \frac{MP_t}{(1+i)^{t+1}} = W_0 + \kappa + \sum_{t=0}^{n-1} \frac{W_t}{(1+i)^{t+1}} \tag{9}$$

Letting G be the present value of the return collected by the firm from training, then function (10) becomes the underlying function to be estimated.

$$MP' + G = W + C \tag{10}$$

4.2. Household Behaviour and Decision-making Theory

Becker developed the theoretical framework on how households make decisions [69] while [11, 58, 67, 51] illustrated its usage. Two types of household decision-making models are classified as unitary and non-unitary and have been used to investigate decisions on child schooling. Unitary models assume that household members have similar preferences and pool their resources to maximise a single household utility function [11, 69]. Non-unitary models consider that households consist of different members with distinct preferences from each other but make decisions in consideration of full cooperation and conflict so that the allocations are Pareto efficient [15, 67, 51]. The non-cooperative methods of the non-unitary models borrow from the concept of Cournot-Nash Equilibrium [15].

4.3. Two Period Consumption Theory

The theoretical literature assumes that CTs confers both an income and a price effect to the recipient households. According to [26], the CTs cause a price effect due to a reduction in shadow wages of children occupying their time in activities other than schooling while an income effect is due to the CTs increasing the household total income. The authors contemplate a two-period model that has in the first period children who allocate their time between work, leisure and schooling. In the second period, the children are adults who choose between work and leisure and earn a wage that is commensurate to the level of schooling in the first period.

In each period, we assume that there are diminishing marginal returns on the utility of consumption and leisure, which are taken to be normal goods. In the second period, schooling is assumed to have diminished marginal productivity on the wage rate. Schooling only provides technological transfer between the two periods and has no direct utility except its effect on the increase in the wage rate in the second period.

4.4. Model Specification

This study uses propensity score matching (PSM), a quasi-experimental design to evaluate the impact of CTs on children school enrolment and attendance by gender in Kenya and follows [78] in methodological design. Quasi-experimental (non-randomized) design and experimental designs have been used to evaluate CTs in Sub-Saharan Africa (SSA). A review of methodological approaches by [72] noted that the practice is consistent to CTs evaluation approaches used in Latin America. The quasi-experimental design adopted for this study, allows for impact evaluation of programmes in the absence of random assignment. The design involves the creation of a comparison (control) group as it is not possible to randomize households into treatment or control groups after the intervention. The control group has similar baseline characteristics to the treatment group [52, 10]. The control group depicts the counterfactual effects if the CT programme had not been implemented.

In order to delineate the two groups, [52, 10] set two imaginary world states that represent the state of being with and without the treatment effect, denoted by 1 and 0, respectively. Let C represent a person in the quasi-experiment, where C=1 represents an individual who receives the treatment (CTs) and C=0 for a person who did not receive the treatment. Let the outcome of the treatment be Y_1 and that of the untreated as Y_0. Then, there exists Y ϵ (Y_1, Y_0) that represents the outcome that is associated with each person in each state. Since any one person can only be in one state at a time, only one potential outcome can occur at any given point in time. The outcome that can be observed is represented by function (11).

$$Y = CY_1 + (1 - C)Y_0 \tag{11}$$

The change in outcome of an individual moving from one state to the other is represented by function (12).

$$\Delta Y = Y_1 - Y_0 \tag{12}$$

Since only one state is observed at a time, the treatment effect cannot be directly observed hence it requires solving the missing data problem. To solve the missing data problem, PSM is used. The PSM creates a valid control group for comparison with treatment group. It is widely used in impact evaluation literature in the absence of experimental data. It corrects for biases in treatment effect due to observed covariates, that result from confounding due to non-random assignment of the treatment [61, 36].

4.4.1. Binary Logit Model

The Logit model for child schooling equation was used to explore the potential impact of CT on the probability of child enrolling and of a child attending school, controlling for a set of observable covariates. The logit model is represented in function (13).

$$Pr(y_i = 1|X) = \Lambda(\beta_0 + \textstyle\sum_{i=1} \beta_i X_i + \lambda T_i) \tag{13}$$

Where y_i =1 if the child is enrolled, y_i =0 otherwise; yi =1 if the child is attending, y_i =0 otherwise; β_i are unknown parameters; X_i is child household and environmental characteristics.; T_i is a dummy variable for receipt of CT; Λ is the cumulative logistic distribution. However, cash transfers are not randomly assigned. This means the estimate of λ would be biased. In the next section, a PSM methodology is outlined to address this problem.

4.4.2. Propensity Score Matching Methods

The PSM methodology creates experimental conditions using observational data where beneficiaries and non-beneficiaries of a treatment are not randomly selected to permit estimation of a causal relationship between outcome and treatment variables [64]. The problem is unobserved counterfactuals, that is, the outcome for non-beneficiaries had they been treated and the outcome for beneficiaries had they not been treated are not observable.

The key feature of PSM procedure is to match individuals on their propensity score that represents their likelihood of being in treatment group given their observable characteristics [61, 36]. Conditioning on observable variables in PSM eliminates the bias [10]. The average difference in the outcomes of interest between treatment and control group can then be estimated. The PSM procedure rests on the assumptions of common support and conditional independence [59].

The conditional independence assumption is that there exists a set of covariates, X, that are not affected by participation so that the probable outcome is not dependent on the treatment. Consequently, the expected outcome would be given by function (14).

$$E[(Y(1)_{t=0}|X,T=1)] = E[(Y(0)_{t=0}|X,T=0)] \quad (14)$$

Thus, conditional on observable covariates, the expected outcome of non-treated is identical to that of the treated, had they not been treated. The assumption of common support necessitates the propensity score to be bounded between 1 and 0.

Several matching techniques are available characterized by trade-off between bias and efficiency [59]. These include nearest-neighbour, calliper/radius, and kernel/local linear techniques. PSM weights the characteristics of control group observations using weights equal to the inverse of their propensity score while characteristics of treatment group have a weight equal to one. This means larger weights on control variables that are similar to the treatment group and lower weights on control observations that are not similar to treatment group.

We estimated the conditional probability of receiving CT or the propensity scores P(x) using observed covariates (x) and a logit model. Individuals with similar observable characteristics are expected to have similar propensity scores, even if their household did not receive CTs. Comparable groups are constructed using their similarity in propensity scores. The comparable groups are individuals with similar propensity scores P(x) but where one group received CTs while the other did not receive a CT. Once the propensity scores are obtained the mean outcome for each group is calculated. The estimated impact of CTs, referred to as the average treatment effect on the treated (ATT) is computed as the difference in average outcomes between the treated and non-treated.

4.5. Definition of Variables

Table 1 presents the variables used in this study of the impact of CTs on children school enrolment and attendance. These variables are divided into dependent variables and covariates. The covariates are based on the existing literature and available data.

Table 1. *Definition of variables.*

Variables	**Definitions**	**Justification of Variables**
Dependent Variables		
School attendance	=1 if attending school and 0 otherwise.	Variable capable of explaining HCD in children schooling. CTs have an effect of improving school attendance.
School enrolment	=1 if enrolled in school and 0 otherwise.	Variable capable of explaining HCD in children schooling. CTs are likely to increase school enrolment.
Explanatory Variables		
Household received CTs	=1 if treated, 0 otherwise	The household that receives CTs can smoothen its consumption, produce human capital and undertake interventions that reduce poverty and improve gender differences at the same time have children in school.
Age of child	Number of years the child has lived	Older children are likely to enrol and attend school.
Gender of the child	=1 if a girl child, 0 otherwise	Gender differences likely to worsen enrolment and attendance. Girls likely to experience low enrolment and attendance rates and likely to be discriminated against in the receipt of CTs
Gender of household head	=1 for Female Headed Household and 0 otherwise	Gender of household head is important in determining CT expenditures. Female Headed Households likely to experience worse enrolment and attendance rates. It is expected that CTs are distributed in a gender sensitive manner.
Parental level of Education	=1 for mother with low level of education and 0 otherwise =1 for father with low level of education and 0 otherwise	Low education of the mother or father is detrimental to child school enrolment and attendance. Expected that parents with low level of education likely to receive CTs as they have limited opportunities
Teenage pregnancies	=1 for teen pregnancies and 0	Teenage pregnancies are likely to affect school enrolment and

Variables	Definitions	Justification of Variables
	otherwise	attendance while CTs are important in keeping young girls in school after early pregnancies.
Early marriage	=1 for early marriage and 0 otherwise	Early marriages are likely to affect school enrolment and attendance while CTs are important in keeping young girls and boys in school and protecting them from early marriages.
Child labour	=1 if in paid employment and domestic work and 0 otherwise	Child labour is likely to affect school enrolment and attendance while CTs might reduce the demand for employment activities that hinder children schooling. Twin impact of CTs on increased school enrolment and reduced domestic work for both boys and girls.
Area of residence	= 1 if Rural and 0 otherwise	Rural residence likely to slow school enrolment and attendance while CTs are expected to impact the lives of children in rural areas as poverty is rampant in these areas. It's expected that the rural children are likely to receive CTs.
Poverty status of the household	= 1 if resides in a poor household and 0 otherwise	Poverty is associated with the number of children not enrolled or attending school as it displaces them from school. It's expected that poor children are more likely to receive CTs.

Source: Author's definitions from reviewed literature

5. Empirical Analysis; Data Sources, Sample Size, Results and Discussions

The study asks whether there are gender differences in children school enrolment and attendance and whether any impact of CTs on these educational outcomes differ between boys and girls in Kenya. Econometric analyses were carried out to answer the research questions. We apply the same methodologies across three samples of pooled, girls' only and boys' only to investigate the impact of cash transfers through a gender lens. The study used the most recent representative household-level data from the Kenya Integrated Household Budget Survey (KIHBS), conducted by the KNBS in Kenya and published in 2017. KNBS describes KIHBS as a source of rich data that was conducted over a period of 12-months across the country [20, 73].

5.1. Sample Size

The study classified households that received Kenya government CTs as treatment group and those that did not receive the CT as the control group. We further demarcated the children educational outcomes into enrolled or otherwise and according to whether or not they had attended school by boys and girls. The pooled sample has 3,000 children as participants while 30,527 are non-participants, giving a total of 33,527 children of school-going age. Of these children, 16,479 are girls comprising of 1,473 in the treatment and 15,006 in the control group while 17,048 are boys comprising of 1,527 in the treatment and 15,521 in the control group.

5.2. Descriptive Statistics: Gender Differences of Children Enrolled or Not Enrolled in School

Gender differences in children school enrolment as presented in Table 2 show the mean probability of children living in poor households not to be statistically different in the treatment between male and female children while it is statistically different at one percent between them in the control, indicating the effect of CTs in reducing gender poverty differences. Noticeable significant variations are recorded between the average age of boys and girls at five and one percent in the treatment and control groups, respectively, indicating late school enrolment for boys. The difference in probability in early marriages between boys and girls shows a statistical significance at one percent only in the non-participating group. The results also indicate significant variations in the probability of child labour at five and one percent between male and female children in the participation and non-participation groups, respectively confirming that there is high participation by boys in child labour.

The results further indicate that there are significant variations between enrolled male and female children in both groups in Female Headed Households (FHHs). In the treatment and control groups, the differences are statistically significant at five and 10 percent, respectively, with girls having a higher probability of living in FHHs. Further, it is observed that girls have statistical and significant differences compared to boys when the data is analysed through the parent's level of education. There is a one percent significant difference between enrolled girls and boys when the data is analysed through the mothers' education. For the fathers' education, there is a five percent significant variation between male and female children in the treatment with female children having a higher probability of the father having low education.

Table 2. Descriptive statistics by treatment status and gender: children enrolled or not enrolled in school.

Variables	TREATMENT			CONTROL		
	Boys	Girls	Diff	Boys	Girls	Diff
	Mean	Mean	diff	Mean	Mean	diff
Poverty status of the household	0.559	0.529	0.030	0.470	0.443	0.026
	(0.014)	(0.014)	(0.019)	(0.004)	(0.004)	(0.006) ***
Area of residence	0.622	0.645	-0.023	0.687	0.688	-0.001
	(0.013)	(0.013)	(0.019)	(0.004)	(0.004)	(0.005)
Age of Child	13.072	12.770	0.303	11.672	11.542	0.130
	(0.101)	(0.104)	(0.145) **	(0.030)	(0.031)	(0.043) ***
Early marriage	0.000	0.000	0.000	0.000	0.002	-0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000) ***
Child labour	0.131	0.102	0.028	0.160	0.119	0.041
	(0.009)	(0.008)	(0.012) **	(0.003)	(0.003)	(0.004) ***
Gender of household head	0.390	0.429	-0.039	0.339	0.348	-0.010
	(0.013)	(0.014)	(0.019) **	(0.004)	(0.004)	(0.006) *
Mother's level of education	0.328	0.407	-0.080	0.529	0.545	-0.016
	(0.013)	(0.014)	(0.019) ***	(0.004)	(0.004)	(0.006) ***
Father's level of education	0.178	0.210	-0.032	0.345	0.343	0.002
	(0.010)	(0.011)	(0.015) **	(0.004)	(0.004)	(0.006)

Standard errors (SE) are in parenthesis. ***, **, * are significant levels at 1%, 5% and 10%, respectively.

5.3. Descriptive Statistics: Gender Differences of Children Attending or Not Attending School

Gender variations among boys and girls attending school between the treatment and control groups in 2015/16 are presented in Table 3. Unlike children enrolment where most variables were significant, the same variables are not significant between girls and boys in the control and treatment groups. The difference in the likelihood of children living in poor households is significant at 10 percent in the treatment that may be associated to the effect of CTs while it is one percent in the control group.

The age of school-going children is significant at 10 per cent and one percent for boys and girls in the groups, respectively. There are differences between boys and girls in the treatment and control groups if the household head is female. The analysis indicates that in the treatment group, there is a five percent significance in the difference of probabilities that girls live in FHH. In the control group, there is 10 percent significant difference in variation of probabilities that girls live in FHH. For parental education, there is a statistical significance that girls are more likely than boys to live in a household where a parent possesses low education qualification.

Table 3. Descriptive statistics by treatment status and gender: children attending or not attending school.

Variables	TREATMENT Boys mean	TREATMENT Girls mean	TREATMENT Diff diff	CONTROL Boys mean	CONTROL Girls mean	CONTROL Diff diff
Poverty status of the household	0.555	0.523	0.032	0.466	0.444	0.022
	(0.014)	(0.014)	(0.020) *	(0.004)	(0.004)	(0.006) ***
Area of residence	0.627	0.646	-0.019	0.688	0.694	-0.006
	(0.014)	(0.014)	(0.019)	(0.004)	(0.004)	(0.006)
Age of Child	12.913	12.633	0.280	11.429	11.251	0.178
	(0.103)	(0.106)	(0.148) *	(0.030)	(0.030)	(0.043) ***
Early marriage	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Child labour	0.112	0.091	0.021	0.136	0.099	0.037
	(0.009)	(0.008)	(0.012) *	(0.003)	(0.003)	(0.004) ***
Gender of household head	0.387	0.427	-0.040	0.336	0.346	-0.010
	(0.014)	(0.014)	(0.020) **	(0.004)	(0.004)	(0.006) *
Mother’s level of education	0.331	0.406	-0.075	0.531	0.546	-0.015
	(0.013)	(0.014)	(0.019) ***	(0.004)	(0.004)	(0.006) **
Father’s level of education	0.178	0.212	-0.033	0.346	0.346	0.000
	(0.011)	(0.012)	(0.016) **	(0.004)	(0.004)	(0.006)

SE are in parenthesis. ***, **, * are significant levels at 1%, 5% and 10%, respectively.

5.4. Impact of CTs on Children School Enrolment

The regressions are carried out using logit and PSM estimators to check for robustness of the results and address the issues of quasi-experimental design biasness and unconfoundedness. The first regression represents the pooled sample between female and male children; the second represents the female only while the third is that of male only.

5.4.1. Logit Regression Results

The logit regression estimates and the marginal effects for the regressors for children school enrolment between the three samples in 2015/16 presented in Table 4 show that CTs are important in addressing gender disparities in enrolment with significant effects in both girls and boys. The results show that CTs affect both female and male children positively with higher effects for male children (-0.420) than female children (-0.330). The positive effect on school enrolment for the male children may be attributed to the fact that there is preference accorded to them by households.

Estimation of the pooled logit model indicates that gender differences are also important in explaining large effects on children school enrolment. The gender of the child variable has a negative marginal effect (-0.328) that is significant at one percent indicating that Kenya is narrowing the gender gap in enrolment between female and male children. Similarly, the gender of the household head is important in explaining children school enrolment as it indicates negative impacts for the pooled (0.426), female (0.521) and male (0.322) samples that are significant at one percent. The poverty and residence variables show positive effects with significance being established at one percent for all the samples. The result therefore establishes that poverty and rural areas are becoming drivers for children school enrolment as the parents in these clusters are realizing the importance of schooling as it can reduce the intergenerational poverty quagmire.

Table 4*. Binomial logit estimates: Enrolment equation.*

Variables	Pooled Sample		Girls Sample		Boys Sample	
	Coef.	**dy/dx**	**Coef.**	**dy/dx**	**Coef.**	**dy/dx**
Household received CTs	-0.366 (0.068) ***	-0.020 (0.004) ***	-0.330 (0.096) ***	-0.019 (0.006) ***	-0.420 (0.098) ***	-0.021 (0.005) ***
Gender of the child	-0.328 (0.047) ***	-0.018 (0.003) ***				
Gender of household head	0.426 (0.051) ***	0.023 (0.003) ***	0.521 (0.071) ***	0.030 (0.004) ***	0.322 (0.074) ***	0.016 (0.004) ***
Poverty status of the household	-1.358 (0.053) ***	-0.073 (0.003) ***	-1.393 (0.073) ***	-0.080 (0.004) ***	-1.329 (0.079) ***	-0.066 (0.004) ***
Area of residence	-0.905 (0.063) ***	-0.049 (0.003) ***	-0.952 (0.086) ***	-0.055 (0.005) ***	-0.859 (0.093) ***	-0.043 (0.005) ***
Age of child	0.595 (0.044) ***	0.032 (0.002) ***	0.580 (0.061) ***	0.033 (0.003) ***	0.622 (0.065) ***	0.031 (0.003) ***
Age of child squared	-0.020 (0.002) ***	-0.001 (0.000) ***	-0.020 (0.003) ***	-0.001 (0.000) ***	-0.020 (0.003) ***	-0.001 (0.000) ***
Child labour	-1.343 (0.058) ***	-0.072 (0.003) ***	-1.192 (0.084) ***	-0.069 (0.005) ***	-1.495 (0.082) ***	-0.075 (0.004) ***
Mother’s level of education	2.387 (0.082) ***	0.128 (0.005) ***	2.506 (0.116) ***	0.144 (0.007) ***	2.268 (0.116) ***	0.113 (0.006) ***
Father’s level of education	1.257 (0.080) ***	0.068 (0.004) ***	1.279 (0.110) ***	0.074 (0.006) ***	1.235 (0.117) ***	0.062 (0.006) ***
_cons	-0.252 (0.243)		-0.380 (0.333)		-0.505 (0.353)	
Pseudo R-squared	*0.2596*		*0.2647*		*0.2558*	
Log likelihood	*-6319.9557*		*-3278.0613*		*-3028.0007*	
LR chi2 statistics	*0.0000*		*0.0000*		*0.0000*	
Number of obs	33,474	33,474	16,453	16,453	17,021	17,021

SE are in parenthesis. ***, **, * are significant levels at 1%, 5% and 10%, respectively.

5.4.2. Propensity Score Matching Regression Results

Table 5 presents the determinants of receiving cash transfers, which is the first stage regression of the PSM on school enrolment. The result show that gender differences are detrimental in determing CT receipts. The gender of the household head is also important in explaining receipt of CTs for children enrolment. From the analysis, FHHs are discriminated against in the receipt of CTs compared to their male counterparts while discrimination is stronger for FHHs with female children (0.120) than with male children (-0.071). Similar results can be inferred for the poverty status of the household. The likelihood of female children (0.351) in poor households to receive CTs is higher than male children (0.366) living in poor households. School enrolled children residing in rural areas are likely to receive CTs as the result shows a negative marginal effect at one percent significant level while both enrolled female and male children in rural areas are likely to receive CTs compared to children living in urban areas. This may be attributed to better targeting of CTs and the high poverty levels in the rural areas compared to urban areas.

From the analysis, it can be inferred that enrolled school children from parents of low educational levels are likely to receive CTs. Enrolled school children, both female and male, with mothers of low education levels (-0.587) are more likely to receive CTs compared to enrolled school children from fathers of low education levels (-0.574). In both cases, female children from parents of low education are less likely to receive CTs compared to male children from similar parents that may be attributed to discrimination against female children and a patriarchal society.

Table 5*. Logit estimates for PSM analysis: School enrolment.*

Household received CTs	Pooled Sample	Girls Sample	Boys Sample
	Coef.	**Coef.**	**Coef.**
Gender of the child	0.021 (0.039)	-	-
Gender of household head	0.021 (0.044)	0.120 (0.063)	-0.071 (0.061)
Poverty status of the household	0.359 (0.039) ***	0.351 (0.056) ***	0.366 (0.055) ***
Area of residence	-0.133 (0.041) ***	-0.105 (0.059) *	-0.164 (0.058) ***
Age of child	-0.108 (0.038) ***	-0.109 (0.054) **	-0.106 (0.054) **
Age of child squared	0.008 (0.002) ***	0.008 (0.002) ***	0.008 (0.002) ***
Child labour	-0.192 (0.057) ***	-0.169 (0.085) **	-0.203 (0.077) ***
Mother’s level of education	-0.587 (0.043) ***	-0.489 (0.060) ***	-0.689 (0.061) ***
Father’s level of education	-0.574 (0.057) ***	-0.457 (0.080) ***	-0.686 (0.080) ***
_cons	-1.968 (0.222) ***	-2.031 (0.311) ***	-1.891 (0.315) ***
Log likelihood	*-9644.8568*	*-4777.9224*	*-4858.4079*
Number of obs	*33491*	*16462*	*17029*
Prob > chi2	*0.0000*	*0.0000*	*0.0000*
Pseudo R2	0.0428	0.0345	0.0524

SE are in parenthesis. ***, **, * are significant levels at 1%, 5% and 10%, respectively.

The estimated propensity scores in Table 5 may not give an accurate estimate of the ATT of interest. We consider a variety of matches namely the NN, radius, and kernel matching that have large sample sizes and highest total number of balanced covariates. We use all the matching methods in our estimation as none may be superior to the other and as a way to assess the robustness of our estimates. The NN matching pairs enrolled children that are treated with their control counterparts that have closest propensity scores to construct counterfactual outcomes. In the NN matching, all the treated units are paired with their matches leading to poor matches as some treated units might be paired with neighbours with different propensity score [55]. The NN matching might therefore not estimate an accurate ATT as the propensity scores used in the matching might bias the results. The solution to this problem is solved by the Radius and Kernel matching methods.

The Radius matching pairs the treated children with only their control counterparts whose propensity scores fall within a certain predetermined radius of the propensity score of the treated children. We set the radius to be sufficient to allow treated children to be matched with their neighbours in the control group. On the other hand, Kernel matching is premised on a weighted average to pair all the treated children with their control counterparts with similar weights to construct a counterfactual outcome. Higher weights are assigned to observations that provide better matches. The estimated ATT for the pooled, female only and male only samples presented in Table 6 show that the impact of CTs on school enrolment is statistically and economically significant. We notice that the results indicate significant variations at one percent in the ATTs among the treated and control group across all the samples and matching estimators.

Table 6. *ATT estimates: School enrolment.*

Estimator	Sample	Treated	Controls	Diff
pooled sample				
NN (1)	ATT	0.881	0.955	-0.075 (0.012) ***
NN (2)	ATT	0.881	0.951	-0.071 (0.010) ***
NN (3)	ATT	0.881	0.934	-0.054 (0.009) ***
NN (4)	ATT	0.881	0.918	-0.038 (0.009) ***
Radius (0.01)	ATT	0.881	0.909	-0.028 (0.006) ***
Radius (0.005)	ATT	0.881	0.908	-0.028 (0.006) ***
Radius (0.0025)	ATT	0.881	0.907	-0.027 (0.006) ***
Kernel (0.01)	ATT	0.881	0.909	-0.029 (0.006) ***
Kernel (0.005)	ATT	0.881	0.908	-0.027 (0.006) ***
Kernel (0.0025)	ATT	0.881	0.908	-0.027 (0.006) ***
Girls Sample				
NN (1)	ATT	0.875	0.945	-0.069 (0.017) ***
NN (2)	ATT	0.875	0.943	-0.067 (0.014) ***
NN (3)	ATT	0.875	0.923	-0.048 (0.013) ***
NN (4)	ATT	0.875	0.905	-0.030 (0.013) ***
Radius (0.01)	ATT	0.875	0.903	-0.027 (0.009) ***
Radius (0.005)	ATT	0.875	0.904	-0.029 (0.009) ***
Radius (0.0025)	ATT	0.875	0.903	-0.027 (0.009) ***
Kernel (0.01)	ATT	0.875	0.903	-0.028 (0.009) ***
Kernel (0.005)	ATT	0.875	0.903	-0.027 (0.009) ***
Kernel (0.0025)	ATT	0.875	0.902	-0.027 (0.009) ***
Boys Sample				
NN (1)	ATT	0.886	0.965	-0.079 (0.015) ***
NN (2)	ATT	0.886	0.959	-0.073 (0.013) ***
NN (3)	ATT	0.886	0.945	-0.060 (0.012) ***
NN (4)	ATT	0.886	0.931	-0.045 (0.012) ***
Radius (0.01)	ATT	0.886	0.916	-0.030 (0.008) ***
Radius (0.005)	ATT	0.886	0.919	-0.033 (0.008) ***
Radius (0.0025)	ATT	0.886	0.917	-0.031 (0.008) ***
Kernel (0.01)	ATT	0.886	0.917	-0.031 (0.008) ***
Kernel (0.005)	ATT	0.886	0.916	-0.031 (0.008) ***
Kernel (0.0025)	ATT	0.886	0.917	-0.031 (0.008) ***

SE are in parenthesis. ***, **, * are significant levels at 1%, 5% and 10%, respectively.

5.5. Impact of CTs on Child School Attendance

The regressions are also carried out using three models of logit and PSM to create a comparison group to reduce the risk of biasness. Analyses are carried out across the three samples of pooled, female only and male only to investigate the impact of CTs on HCD from a gender perspective.

5.5.1. Logit Regression Results

Unlike the binomial logit results presented on the impact of CTs on children school enrolment that show a direct impact on enrolment, the results of the impact of CTs on school attendance are mixed as presented in Table 7. In the pooled sample CTs show a positive effect on children school attendance that is not statistically significant. The impact of CTs on female children is negative with a positive marginal effect (0.060) that is also not significant while the impact on male children attending school is positive with a negative marginal effect (-0.125) that is also not significant. These results may be attributed to Kenya's patriarchal society where the male child is favoured while the female child is discriminated against due to gender norms.

The discrimination against the female child is not observed in school attendance as female children are provided with an opportunity to attend school as witnessed by the gender indicator that has a negative marginal effect (-0.331) that is significant at one percent. This result may also indicate that the country is bridging the gender gap in school attendance. The results further show that school attending children in FHHs are unlikely to attend school, but it is worse off for female children compared to male children. This confirms the preposition that FHHs face numerous challenges in their pursuit for better opportunities for their families. The results further confirm the assumption that FHHs engage the services of the female child to look after the young ones to allow the mother to fend for the family while the male child is left to attend school with the expectation that he will help the family to overcome the effects of poverty in the future.

It seems poverty is not detrimental to school attendance as the poverty variable has negative marginal effect for all the three samples that are also significant at one percent. This result may explain the realization by poor families that bridging the intergenerational poverty gap may only be through HCD. Other variables that are not a hindrance to school attendance include the rural residence, old age, and child labour while low parental education favours children school attendance from household, where there is low maternal education compared to low paternal education. Proper targeting of CTs to rural households and the Republic of Kenya (2013) could explain the significant effect of rural residence and child labour variables.

Table 7. Binomial logit estimates: School attendance.

Variables	Pooled Sample		Girls Sample		Boys Sample	
	Coef.	dy/dx	Coef.	dy/dx	Coef.	dy/dx
Household received CTs	-0.025	-0.002	0.060	0.005	-0.125	-0.010
	(0.059)	(0.005)	(0.084)	(0.008)	(0.083)	(0.007)
Gender of the child	-0.331	-0.029	-	-	-	-
	(0.038) ***	(0.003) ***	-	-	-	-
Gender of household head	0.270	0.023	0.354	0.032	0.180	0.015
	(0.042) ***	(0.004) ***	(0.059) ***	(0.005) ***	(0.061) ***	(0.005) ***
Poverty status of the household	-0.924	-0.080	-0.930	-0.084	-0.933	-0.077
	(0.039) ***	(0.003) ***	(0.054) ***	(0.005) ***	(0.056) ***	(0.005) ***
Area of residence	-0.313	-0.027	-0.300	-0.027	-0.333	-0.027
	(0.043) ***	(0.004) ***	(0.060) ***	(0.005) ***	(0.063) ***	(0.005) ***
Age of child	1.058	0.091	1.096	0.099	1.027	0.085
	(0.035) ***	(0.003) ***	(0.049) ***	(0.004) ***	(0.051) ***	(0.004) ***
Age of child squared	-0.047	-0.004	-0.049	-0.004	-0.045	-0.004
	(0.001) ***	(0.000) ***	(0.002) ***	(0.000) ***	(0.002) ***	(0.000) ***
Child labour	-1.708	-0.147	-1.623	-0.146	-1.792	-0.148

Variables	Pooled Sample		Girls Sample		Boys Sample	
	Coef.	dy/dx	Coef.	dy/dx	Coef.	dy/dx
	(0.043) ***	(0.004) ***	(0.063) ***	(0.005) ***	(0.060) ***	(0.005) ***
Mother's level of education	1.189	0.103	1.226	0.110	1.159	0.096
	(0.043) ***	(0.004) ***	(0.061) ***	(0.005) ***	(0.063) ***	(0.005) ***
Father's level of education	0.736	0.063	0.821	0.074	0.642	0.053
	(0.053) ***	(0.005) ***	(0.075) ***	(0.007) ***	(0.076) ***	(0.006) ***
_cons	-2.610		-3.077		-2.501	
	(0.197) ***		(0.273) ***		(0.283) ***	
Pseudo R-squared	*0.2028*		*0.2061*		*0.2017*	
Log likelihood	*-9826.3696*		*-4997.3219*		*-4809.0702*	
LR chi2 statistics	*0.0000*		*0.0000*		*0.0000*	
Number of obs	33,474	33,474	16,453	16,453	17,021	17,021

SE are in parenthesis. ***, **, * are significant levels at 1%, 5% and 10%, respectively.

5.5.2. Propensity Score Matching Regression Results

Table 8 presents the determinants of receiving cash transfers, which is the first stage regression of the PSM on school attendance. The results show that the gender of the child attending school is not important in determining receipts of CTs. The gender variable has a positive marginal effect that is not significant indicating that female child competes for the receipt of CTs with the male child without consideration of the challenges faced by female children. Receipt of CTs is also gender blind considering that FHH variable has a positive marginal effect for the pooled sample that is not significant. The likelihood of a female child from a FHH to receive CTs is minimal comparing to a male child from a similar household. Poverty status of a child attending school is also not a consideration for receipt of government CTs. Both the boys' and girls' only samples have negative effects for the poverty indicator that is significant at one percent. Children attending school from rural areas are highly likely to receive CTs compared to children from urban areas due to poverty prevalence in the rural areas. Child labour and education of the parents are important determinants of CTs. This may be a target group of receipt of CTs as the government endeavours to move the less fortunate out of poverty. Female children from either mothers or fathers with low education are less likely to receive CTs compared to their male counterparts.

Table 8*. Logit estimates for PSM analysis: School attendance.*

Household received CTs	Pooled Sample	Girls Sample	Boys Sample
	Coef.	Coef.	Coef.
Gender of the child	0.021 (0.039)		
Gender of household head	0.021 (0.044)	0.120 (0.063) *	-0.071 (0.061)
Poverty status of the household	0.359 (0.039) ***	0.351 (0.056) ***	0.366 (0.055) ***
Area of residence	-0.133 (0.041) ***	-0.105 (0.059) *	-0.164 (0.058) ***
Age of child	-0.108 (0.038) ***	-0.109 (0.054) **	-0.106 (0.054) **
Age of child squared	0.008 (0.002) ***	0.008 (0.002) ***	0.008 (0.002) ***
Child labour	-0.192 (0.057) ***	-0.169 (0.085) **	-0.203 (0.077) ***

Household received CTs	Pooled Sample Coef.	Girls Sample Coef.	Boys Sample Coef.
Mother's level of education	-0.587 (0.043) ***	-0.489 (0.060) ***	-0.689 (0.061) ***
Father's level of education	-0.574 (0.056) ***	-0.457 (0.080) ***	-0.686 (0.080) ***
_cons	-1.968 (0.222) ***	-2.031 (0.311) ***	-1.891 (0.315) ***
Log likelihood	*-9644.8568*	*-4777.9224*	*-4858.4079*
Number of obs	*33491*	*16462*	*17029*
Prob > chi2	*0.0000*	*0.0000*	*0.0000*
Pseudo R2	0.0428	0.0345	0.0524

SE are in parenthesis. ***, **, * are significant levels at 1%, 5% and 10%, respectively.

In assessing the quality of the PSM estimator, we follow the argument outlined for the enrolment case to estimate the ATT as the propensity scores presented in Table 9 may not estimate an accurate ATT. The result presented in Table 9 shows that CTs have an impact that is statistically and economically significant on HCD through school attendance. These results are witnessed by non-significant variations among the treatment and control ATTs across all the samples. Results from the girls' and the boys' only samples, show the intervention to have an impact on school attendance for a few matches.

Table 9. *ATT estimates: School attendance.*

Estimator	Sample	Treated	Controls	Diff.
Pooled Sample				
NN (1)	ATT	0.838	0.855	-0.016 (0.019)
NN (2)	ATT	0.838	0.853	-0.014 (0.014)
NN (3)	ATT	0.838	0.838	0.000 (0.012)
NN (4)	ATT	0.838	0.826	0.013 (0.011)
Radius (0.01)	ATT	0.838	0.836	0.002 (0.007)
Radius (0.005)	ATT	0.838	0.837	0.002 (0.007)
Radius (0.0025)	ATT	0.838	0.834	0.004 (0.007)
Kernel (0.01)	ATT	0.838	0.838	0.001 (0.007)
Kernel (0.005)	ATT	0.838	0.836	0.002 (0.007)
Kernel (0.0025)	ATT	0.838	0.836	0.002 (0.007)
Girls Sample				
NN (1)	ATT	0.839	0.831	0.008 (0.028)
NN (2)	ATT	0.839	0.84	-0.001 (0.021)
NN (3)	ATT	0.839	0.826	0.013 (0.018)
NN (4)	ATT	0.839	0.818	0.022 (0.016) *
Radius (0.01)	ATT	0.839	0.826	0.013 (0.010) *
Radius (0.005)	ATT	0.839	0.828	0.011 (0.010)
Radius (0.0025)	ATT	0.839	0.827	0.012 (0.010)
Kernel (0.01)	ATT	0.839	0.83	0.010 (0.010)

Estimator	Sample	Treated	Controls	Diff.
Kernel (0.005)	ATT	0.839	0.828	0.012 (0.010)
Kernel (0.0025)	ATT	0.839	0.828	0.011 (0.010)
Boys Sample				
NN (1)	ATT	0.838	0.877	-0.039 (0.026) *
NN (2)	ATT	0.838	0.863	-0.026 (0.020) *
NN (3)	ATT	0.838	0.848	-0.011 (0.017)
NN (4)	ATT	0.838	0.832	0.006 (0.016)
Radius (0.01)	ATT	0.838	0.844	-0.006 (0.010)
Radius (0.005)	ATT	0.838	0.852	-0.014 (0.010) *
Radius (0.0025)	ATT	0.838	0.851	-0.013 (0.010) *
Kernel (0.01)	ATT	0.838	0.848	-0.010 (0.010)
Kernel (0.005)	ATT	0.838	0.847	-0.010 (0.010)
Kernel (0.0025)	ATT	0.838	0.851	-0.013 (0.010) *

SE are in parenthesis. ***, **, * are significant levels at 1%, 5% and 10%, respectively.

5.6. Discussion of the Results

A cross check of characteristics of school age going children among the treated and control children indicates that children in the treatment have worse means in nearly all the indicators under considerations. This is also true for the female children when compared to their male counterparts. In the participation group, children have; a lower likelihood of living in the rural areas, high poverty prevelance, lower probability of teenage pregnancies and early marriages, and lower probability of having parents with low education compared to the control group.

The logit regression indicate that CTs are important in addressing gender disparities in enrolment with significant effects in both girls and boys, though the magnitude is higher for the male child. The PSM analysis does not find any impact of CTs on school enrolment but attendance. The divergence between the logit regression and PSM results regarding the impact of CTs on addressing gender disparities in enrolment can be attributed to several methodological factors. First, unobserved confounding may play a role: while PSM aims to balance observed covariates between treated and control groups, it cannot account for unobserved variables that may influence both treatment assignment and outcomes. In contrast, logit regression might partially capture the effects of such unobserved factors through correlated variables [74]. Second, functional form sensitivity could contribute to the discrepancy, as logit regression relies on specific parametric assumptions that, if mis-specified, may bias the results. Third, the two methods estimate different treatment effects: logit regression typically provides average marginal effects across the entire sample, whereas PSM often estimates the average treatment effect on the treated (ATT), which may differ in the presence of treatment effect heterogeneity [75]. Lastly, sample differences may influence the findings, since PSM excludes unmatched units to improve comparability, potentially leading to a different analytic sample than that used in the full-sample logit regression [76].

On the other hand, the logit regression finds that the effect of CTs on attendance is mixed with the result indicating a positive effect for male children while it has a negative effect for the female children. The PSM results indicate that CTs have a positive impact for school attendance for both boys and girls. These results are similar to the findings of [54, 17, 3, 7, 49, 22, 1] who find CTs to influence school enrolment and attendance. Unlike [6, 57], our results find CTs to increase school enrolment and attendance with noticeable gender differences. We also find results similar to those of [46, 4, 2] who found that CTs improved school attendance but differ on the magnitude for girls.

The deviation in findings between the logistic regression and Propensity Score Matching (PSM) approaches regarding attendance outcomes may be attributed to several methodological considerations. First, the logit model may be subject to omitted variable bias if it fails to account for all relevant covariates or interaction effects. This can result in biased or inconsistent estimates, particularly when unobserved heterogeneity influences both treatment assignment and outcomes [74]. Second, the absence of interaction terms, such as those between treatment status and gender, may obscure heterogeneous treatment effects. For instance, if the intervention impacts males and females differently, a model that does not explicitly incorporate these interactions may yield misleading or statistically insignificant results. Third, PSM offers a distinct advantage by explicitly balancing observed covariates between treated and control groups prior to estimation. This matching process mitigates confounding more effectively than a potentially mis-specified parametric model, thereby enhancing the credibility of causal inferences [77]. Finally, the functional form assumptions inherent in logistic regression—specifically, the assumption of a log-linear relationship in the log-odds—may not adequately capture complex or non-linear dynamics in the data. In contrast, PSM is a semi-parametric method that imposes fewer structural assumptions, allowing for greater flexibility in estimating treatment effects. These methodological differences likely contribute to the observed variation in results between the two approaches [76].

Further, our findings from the logit regression suggest that gender differences are not a hindrance to children school enrolment in Kenya as the country is in the process of bridging the gender gap in school enrolment through its targeted policies on gender mainstreaming as outlined in [31, 32]. The PSM regression results indicate that CTs are provided to children's households in a gender biased manner that may weaken the essence of the CTs. These results are not consistent with [34] results that find gender to be a source of educational disparities between children of school-going age. Furthermore, the logit regression findings indicate that gender of the household head is detrimental to children school enrolment and attendance. Our results collaborate [71] who found that children in FHHs are more likely not to be enrolled in school that is worse for female than male children. The PSM results show that issuance of CTs is not gender sensitive.

Additionally, the logit regression results indicate that poverty of a household is not a hindrance to children school enrolment and attendance for both boys and girls due to the government policies and laws that force parents to have children in school. This result is not consistence to [13] who identified poverty to be the major determinant of low school attendance. The rural residence is also not a driver of low school enrolment and attendance. Our results contradict [34] who found poverty, and rural residence to significantly contribute to educational disparities between children of school going age. The PSM regression results reveal that poverty is not a consideration in receiving CTs in both enrolled and attending children that may lead to poor targeting of beneficiaries and low impact of CTs. The results also indicate that school enrolment and attendance is favourable for older children while child labour has no adverse impact on enrolment and attendance similar to [56, 65]. This result contradicts [13] who find poverty to be detrimental to school attendance. Similar to [13], low levels of parental education slow children school enrolment, a result that underscore the intergenerational benefits of HCD.

6. Conclusion and Policy Recommendations

This paper investigated the impact of CTs on HCD through school enrolment and attendance in Kenya. We carried out significance tests between the treated and control groups and between boys and girls. The non-linear and PSM regression models are applied to investigate the impact of CTs on children school enrolment and attendance. Same methodologies were applied across the three samples of pooled, girls' only and boys' only to investigate the impact of CTs through a gender perspective. The results show that there are noticeable variations between children in the treatment and control groups while pockets of gender gap exists between girls and boys. We note that the gender gap in school enrolment and attendance is narrowing but girls are still in a disadvantaged position.

The results show that CTs have an impact on HCD through children school enrolment and attendance in Kenya. The regression results indicate that CTs are important in addressing gender disparities in school enrolment and attendance with significant effects in both girls and boys, though the magnitude is higher for male children. Variables that support school enrolment and attendance are CTs, gender of the child, household poverty, rural residence, and child labour while gender of the household head and educational attainment of the mother and father are detrimental to children school enrolment and attendance. The PSM results indicate that receipt of CTs by households is not pegged on key variables like household poverty and gender. Generally, the findings of the study are consistent with previous studies, which have established that CTs are viable pathways for HCD through children school enrolment and attendance.

The evidence from this study confirms that CTs have achieved some of their objectives of cushioning poor families to overcome income gaps in order to get children into school. However, to effectively disrupt the intergenerational cycle of poverty, building of sufficient human capital through CTs require concerted efforts between the government and stakeholders. We recommend enhancement of the fiscal space for CTs, both in terms of the magnitude of CTs transferred to households and the number of beneficiaries. To sustain the CT programmes and realize the maximum impact, the government should establish governance administrative structures for CTs that are accountable and transparent in their delivery mechanism. In order to bridge the gender gap, gender mainstreaming by the ministry responsible for gender should take centre stage in the allocation of CTs.

Abbreviations

ATT	Average Treatment Effect on the Treated
CT-OVC	Cash Transfer to Orphans and Vulnerable Children

CTs	Cash Transfers
FHHs	Female Headed Households
HCD	Human Capital Development
HCT	Human Capital Theory
HSNP	Hunger Safety Net Programme
NN	Nearest-neighbour
PSM	Propensity Score Matching

Author Contributions

Jared Masini Ichwara is the sole author. The author read and approved the final manuscript.

Data Availability Statement

The data that support the findings of this study can be found at: https://statistics.knbs.or.ke/nada/index.php/catalog/13 (a publicly available repository url that can be requested).

Conflicts of Interest

The author declares no conflicts of interest.

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