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IMPACT OF BENAZIR INCOME SUPPORT PROGRAM ON HOUSEHOLD DEVELOPMENT IN PAKISTAN'S LOWEST INCOME BRACKET

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Abstract
This study assesses how household development differs between Benazir Income Support Programme (BISP) recipient and non-recipient households in Pakistan's bottom 40 percent. Using PSLM-HIES 2018-19 data (n=9,923), it constructs a Household-based Human Development Index (HHDI) by combining living standards, health, and education into a single 0–100 index. Living standards are measured through per-capita expenditure, health through under-five survival and child immunization, and education through mean years of schooling and enrolment. The study compares outcomes using descriptive statistics, OLS regressions with household and location controls, and propensity score matching (kernel) to improve comparability on observable characteristics. Results show that BISP recipient households have lower average HHDI scores than non-recipients, mainly due to lower living standards and weaker education outcomes, while health differences are small and not statistically significant. After adjustment, the gaps reduce but remain for HHDI and living standards, and education differences become smaller.
Keywords: Household-based HDI, BISP, Unconditional cash transfer, Living standard, Health, Education

1. Introduction

In today's global landscape, attaining economic development is considered the paramount objective for countries around the world. The long-term economic development requires strategies that not only boost economic growth but also warrant sustainability and equity. However, Pakistan has struggled to implement strategic measures to sustain desired economic development. Pakistan ranks 164th in the human development index (HDI) with a value of 0.540, a significantly below the global average of 0.739 (Pakistan Economics Survey, 2024, pg. 258). Pakistan has lowest HDI in the South Asian region with an exception to Afghanistan.

The lower level of HDI underscore the challenges in the economic growth, health, and education outcome. The reason behind the lower HDI can be attributed to multifaceted factors, yet poverty remains a crucial contributing factor. Pakistan with its 40 per cent poverty rate struggles to excel in human development (Chishti et al., 2022). Nonetheless, the impact of poverty can be soften by implementing effective social protection programs (SPPs)– encompasses social safety net/social assistance, social insurance, and labour market programs (Barrientos, 2011). Social safety programs (SSPs) not only helps in reducing poverty but also acts as a buffer against recession. Globally, 1.54 per cent of GDP is spent on SSPs (FAO et al., 2021). Developing economies allocate 1.5 per cent, while high income nations spend 2.2 per cent. In contrast, Pakistan spends only 0.58 per cent, which is below the South Asian region's average of 0.9 per cent.

Among the SSPs of Pakistan, Benazir Income Support Program (BISP) is a more comprehensive and well-organized unconditional cash transfer program that commenced in 2009 with 15.85 billion PKR and 1.76 million beneficiaries (Pakistan Economics Survey, 2024). Since commencing of BISP, the cash transferred and beneficiaries have increased to PKR332.91 billion and 9 million in 2023. Recognizing the importance of such an unconditional cash transfer program, this study aims to assess the impact of BISP on the development of

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recipient households. This study is one of the few studies in the existing literature that examines the developmental effects of BISP at household level.

Household-level human development matters for poverty and inequality analysis because deprivations are experienced jointly within the same family, through housing quality, basic services, schooling, and health risks that interact over time. Aggregate summaries, and even individual indicators, can miss how disadvantages cluster within households and how resources are shared across members. This limitation is especially relevant for the bottom 40 per cent, a policy-relevant segment where small differences in living conditions can coincide with large differences in capabilities and vulnerability. Evidence from social protection and poverty research in Pakistan repeatedly points to meaningful welfare variation among households that are all considered poor by design or targeting criteria (Durr-e-Nayab & Farooq, 2014; Ali, 2015; Ali & Rehman, 2015Jamil, 2024).

Evidence from Pakistan's social protection literature also underlines why a careful, household-level comparison between recipients and non-recipients can be informative without being framed as causal (Sajid & Ali, 2018; Shair et al., 2023a; 2023b; Marc et al., 2023). Targeting processes can differentiate who becomes a beneficiary, and comparisons between politically identified beneficiaries and those selected through a poverty scorecard suggest meaningful socioeconomic differences across recipient groups, including residential conditions and income profiles (Ali & Afzal, 2019; Waqas and Torre, 2020). At the same time, broader assessments of BISP describe how limited transfer amounts may be absorbed by immediate consumption needs, leaving less scope for measurable gains in education and health outcomes (Mumtaz and Whiteford, 2017; Bibi & Ali, 2021). Micro-evidence from rural Peshawar similarly reports that most beneficiary households allocate transfers to basic necessities such as food and children's education, with only a small minority engaging in business activity (Naushad et al., 2025a).

Even so, much of the existing work examines development outcomes in separate silos. Studies track fuel and energy choices among ultra-poor households, but do not jointly summarise education and health conditions (Nawaz & Iqbal, 2020). Others focus on access to health services or specific health-related outcomes (Waqas & Awan, 2018), or examine education gaps such as gender disparity without embedding them in a broader household development profile (Zulfiqar et al., 2024). Parallel strands emphasise empowerment and social outcomes, again typically as single dimensions (Waqas & Awan, 2019; Iqbal et al., 2020; Ahmad et al., 2021; Naseer et al., 2021). This fragmentation motivates an integrated household-based index that can summarise multiple dimensions together for poor households.

A comparative lens between recipient and non-recipient households is analytically useful because it documents development differentials within the same lower segment of the distribution. The goal is descriptive and associational, not causal. Receipt status can coincide with different household profiles in living standards, schooling, and health-related conditions, even among households that are all relatively poor. Empirical work on beneficiary households in rural settings similarly highlights that socio-economic outcomes vary across households within the same broad low-income context, suggesting meaningful heterogeneity that a composite measure can make visible (Naushad et al., 2025b).

The objective of the study is two-fold. Initially, it estimates the household-based human development index (HHDI), which is a composite of living standards, health and education outcomes for the bottom 40 per cent households of in the distribution. Subsequently, the study compare the HHDI and its sub-indices (living standards, health and education) amongst the recipient and non-recipient households. The findings of the study crucial for policy makers, researchers and development economists in refining and enhancing BISP and in the broader assessment of policy interventions. By integrating domains that are often studied separately and applying a household-based composite approach to a policy-salient population, the study fills an empirical and measurement gap in the existing evidence base.

2. Methodology

2.1. Data Source

The study utilizes Pakistan Social and Living Standard-Household Integrated Economic (PSLM - HIES 2018-2019) Survey, sourced from the official website of the Pakistan Bureau of Statistics (PBS). The survey covers

24,809 households across the Pakistan. However, our study specifically focuses on the bottom 40 per cent of these household, which consist only 9,923 households.

2.2. Construction of outcome variables

The household-based human development index (HHDI) constructed from the living standards, health and education outcomes. The living standards proxy by expenditure per capita. The health outcome assessed by under-five child survival rate with a two-third weight and child immunization rate with one-third weight (Jamal & Khan, 2007). The education outcome determined by mean year of schooling with a two-third weight, and enrolment rate with a one-third weight (Qasim et al. 2017). The sub-indices of HHDI was transformed into a scale of 0 to 1 rage by employing max-min UNDP approach. The simple arithmetic mean was used to derive HHDI from the sub-indices.

Let h index households. You construct three sub-indices: living standards (LS), health (H), and education (E), each transformed to $[0, 1]$using the UNDP min–max normalization:

$$I_{dh} = \frac{X_{dh} - \min(X_d)}{\max(X_d) - \min(X_d)} d \in \{LS, H, E\}$$

Living standards are proxied by per-capita expenditure:

$$X_{LSh} = \mathrm{PCE}_h \Rightarrow LS_h = I_{LSh}$$

Health is based on under-five survival (weight $2/3$) and immunization (weight $1/3$) (Jamal & Khan, 2007):

$$H_h = \frac{2}{3} I(\mathrm{U5Survival}_h) + \frac{1}{3} I(\mathrm{Immunization}_h)$$

Education is based on mean years of schooling (weight $2/3$) and enrolment rate (weight $1/3$) (Qasim et al., 2017):

$$E_h = \frac{2}{3} I(\mathrm{MYS}_h) + \frac{1}{3} I(\mathrm{Enrolment}_h)$$

Finally, HHDI is the simple arithmetic mean of the three sub-indices:

$$HHDI_h = \frac{1}{3}(LS_h + H_h + E_h)$$

2.3. Econometric model

2.3.1. Ordinary Least Square Model

To compare recipient and non-recipient households, estimate separate OLS regressions with each outcome $Y_h \in \{HHDI_h, LS_h, H_h, E_h\}$:

$$Y_h = \alpha + \beta\, BISP_h + \gamma' X_h + \varepsilon_h$$

- $BISP_h$is an indicator equal to 1 if the household receives BISP and 0 otherwise.
- $X_h$is a vector of controls and location fixed effects.

Given your table, $X_h$includes:

- Province indicators (with one omitted reference province): KPK_h, $Punjab_h$, $Sindh_h$
- Urban dummy: $Urban_h$
- Dependency ratio: $DepRatio_h$
- Head characteristics: $HeadMale_h$, $HeadEduc_h$

So the fully written model consistent with your output is:

$$\begin{aligned} Y_h = \alpha + \beta BISP_h + \delta_1 KPK_h + \delta_2 Punjab_h + \delta_3 Sindh_h + \theta Urban_h + \phi DepRatio_h + \psi HeadMale_h \\ + \omega HeadEduc_h + \varepsilon_h \end{aligned}$$

Interpretation (for the OLS table): $\beta$is the conditional mean difference in the outcome between BISP recipients and non-recipients after adjusting for covariates, not an impact estimate. The definition of variables used in the study is presented in table 1.

2.3.2. Propensity Score Matching (PSM) model

Estimate the probability of receiving BISP using a logit or probit:

$$p(X_h) = \Pr(BISP_h = 1 \mid X_h) = F(\kappa + \lambda' X_h)$$

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where $F(\cdot)$is the logistic (or normal) CDF.
Define potential outcomes $Y_h(1)$and $Y_h(0)$. The parameter of interest is typically the ATT:

$$ATT = \mathbb{E}[Y_h(1) - Y_h(0) \mid BISP_h = 1]$$

Under conditional independence and common support:

$$ATT = \mathbb{E}[\, \mathbb{E}(Y_h \mid BISP_h = 1, p(X_h)) - \mathbb{E}(Y_h \mid BISP_h = 0, p(X_h)) \mid BISP_h = 1]$$

An operational matching estimator (generic form) is:

$$\widehat{ATT} = \frac{1}{N_1} \sum_{h \in T} \left(Y_h - \sum_{j \in C} w_{hj} \, Y_j \right)$$

- T is the set of treated (recipients), Ccontrols (non-recipients).
- w_{hj} are matching weights (nearest neighbor, kernel, radius, etc.), with $\sum_{j \in C} w_{hj} = 1$.

PSM rationale can be phrased as: it aims to replicate a randomized comparison by balancing observable characteristics (Li, 2013).

Table 1: Definition of variables

Variable	Definition / Construction	Unit / Coding
HDI (HHDI)	Composite Household-based Human Development Index combining the three sub-indices: Living, Health, and Education at household level. Higher value indicates better household human development.	0–100 (index score)
Living	Living standards sub-index of the HHDI capturing household living conditions/standard of living. Higher value indicates better living standards.	0–100 (index score)
Health	Health sub-index of the HHDI reflecting household health-related outcomes/conditions. Higher value indicates better health status/access conditions.	0–100 (index score)
Education	Education sub-index of the HHDI reflecting household education-related outcomes/attainment conditions. Higher value indicates better education status.	0–100 (index score)
BISP	Household is a BISP recipient (receives cash transfer/benefit) indicator.	Binary: 1 = Yes, 0 = No
KPK	Household located in Khyber Pakhtunkhwa (KPK) (province dummy).	Binary: 1 = KPK, 0 = otherwise
Punjab	Household located in Punjab (province dummy).	Binary: 1 = Punjab, 0 = otherwise
Sindh	Household located in Sindh (province dummy).	Binary: 1 = Sindh, 0 = otherwise
Urban	Household resides in an urban area.	Binary: 1 = Urban, 0 = Rural
Dep ratio	Dependency ratio within the household (share of dependents relative to working-age members), expressed as a percentage. Higher values indicate higher dependency burden.	0–100 (percent)
Male	Household head gender indicator (male-headed household).	Binary: 1 = Male head, 0 = Female head
Literate head	Household head is literate (can read and write) indicator.	Binary: 1 = Literate, 0 = Not

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		literate

3. Results and Discussion

Table 2 provides a clear snapshot of both the overall distribution of human development in the sample and how it differs by BISP receipt status. At the aggregate level, the mean HDI is 59.3 (out of 100), with households scoring relatively higher on Health (81.4) and Living standards (71.4) than on Education (25.2). This contrast is informative for understanding the sample's deprivation profile. On average, education outcomes appear to be the weakest dimension, and the large spread in Education (Std. Dev. 20.1) suggests substantial heterogeneity across households, even before splitting by BISP status.

When comparing recipients and non-recipients, Table 2 shows that BISP receipt is associated with lower composite human development. Recipient households have a lower mean HDI than non-recipients (57.0 versus 59.7). The underlying pattern is not uniform across dimensions. The largest difference is in Education, where recipients average 21.4 compared to 25.9 among non-recipients, indicating that recipient households tend to have weaker schooling-related outcomes. A similar, though smaller, gap appears in Living standards (68.8 for recipients versus 71.8 for non-recipients). In contrast, the Health sub-index is high for both groups and differs only slightly (80.8 versus 81.5), suggesting that health-related outcomes in this sample vary less by receipt status than education and living standards do.

The table also signals meaningful differences in sample composition across provinces and rural-urban location. Overall, the sample is concentrated in Punjab (mean 0.43), followed by Sindh (0.25) and KPK (0.20). However, recipients are disproportionately located in Sindh and KPK, with much lower representation in Punjab. Specifically, the mean share of KPK is higher among recipients (0.31 versus 0.18), and Sindh is also higher among recipients (0.42 versus 0.22), while Punjab is notably lower among recipients (0.23 versus 0.47). This matters because provincial context is often correlated with service availability, labour markets, and household welfare profiles, meaning that part of the observed HDI gap could reflect geographic composition rather than only household-level differences. Similarly, recipients are less urban (0.12) than non-recipients (0.17), indicating that BISP households in this sample are more rural on average. Given that rural households typically face different constraints around schooling access, service delivery, and earnings opportunities, this rural skew can plausibly align with the lower education and living standards indices observed among recipients.

Household structure and head characteristics show a mix of similarities and contrasts. The dependency ratio is broadly comparable across groups (46.9 for recipients versus 47.8 for non-recipients), suggesting that age composition and household burden are not sharply different on average. Male headship is very high overall (0.93) and identical across groups, so gender of household head does not appear to distinguish recipients from non-recipients in this sample. One striking difference is head literacy: recipients show a higher mean for literate household head (0.66) than non-recipients (0.58). This does not contradict the education disadvantage in the education sub-index, because head literacy captures one adult attribute, whereas the education index reflects broader household schooling outcomes (mean years and enrolment). Still, it signals that the recipient and non-recipient groups differ along multiple dimensions, not only welfare levels.

Overall, Table 2 suggests that recipient households are a systematically different group: they are more rural, more concentrated in Sindh and KPK, and tend to have lower HDI levels, particularly due to education and (to a lesser extent) living standards, while health differences are relatively small. These baseline contrasts are important for the empirical strategy because they imply that simple mean comparisons may partly reflect selection/targeting and geographic composition. This is exactly why later analysis needs controls for province, urban location, and household characteristics, and why any recipient-non-recipient comparisons should be interpreted as descriptive and associational rather than causal.

Table 2: Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Mean (BISP = 1)	Mean (BISP = 0)
HDI	9,923	59.31	12.29	0	100	56.99	59.73
Living	9,923	71.36	18.20	0	100	68.80	71.82

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Health	9,923	81.38	17.89	0	100	80.79	81.48
Education	9,923	25.20	20.09	0	100	21.41	25.88
BISP	9,923	0.15	0.36	0	1	1	0
KPK	9,923	0.20	0.39	0	1	0.31	0.18
Punjab	9,923	0.43	0.49	0	1	0.23	0.47
Sindh	9,923	0.25	0.44	0	1	0.42	0.22
Urban	9,923	0.16	0.37	0	1	0.12	0.17
Dep ratio	9,923	47.67	20.48	0	100	46.85	47.82
Male	9,923	0.93	0.26	0	1	0.93	0.93
Literate head	9,923	0.59	0.49	0	1	0.66	0.58

Table 3 reports two-sample t-tests that compare average outcomes between non-recipient (BISP=0; n=8,426) and recipient households (BISP=1; n=1,497). The "mean diff (0–1)" should be read as mean(BISP=0) minus mean(BISP=1), so a positive value indicates that non-recipients have a higher sample mean. With equal variances assumed, the test indicates whether the observed mean gap is statistically distinguishable from zero in this sample.

Across the composite index and key sub-indices, the main pattern is that BISP-recipient households have lower average scores. The HHDI mean is 59.73 for non-recipients versus 57.00 for recipients, a gap of 2.73 points that is statistically significant (t=7.93, p=0.000). Similar differences appear for Living standards (71.82 vs 68.80; diff=3.02, p=0.000) and Education (25.88 vs 21.41; diff=4.47, p=0.000), with the education gap being the largest in absolute terms. Given the 0–100 scale, these gaps are modest in size, but they are consistent and precisely estimated. By contrast, Health is high for both groups and the mean difference is small (0.70), and it is not statistically significant (t=1.39, p=0.166), implying that the data do not provide strong evidence of a systematic health mean gap by receipt status. Overall, these differences should still be interpreted cautiously because receipt status likely reflects selection/targeting, which is why multivariate controls are essential in subsequent analysis.

Table 3: Mean Differences in HHDI and Sub-Indices by BISP Receipt (Two-Sample t-tests)

Outcome (HHDI & sub-indices)	Non-recipient (BISP=0) Mean (SD)	Recipient (BISP=1) Mean (SD)	Mean diff (0−1)	t-stat	p-value
HHDI	59.73 (12.52)	57.00 (10.63)	2.73	7.93	0.000
Living standards	71.82 (18.15)	68.80 (18.32)	3.02	5.92	0.000
Education	25.88 (20.49)	21.41 (17.22)	4.47	7.95	0.000
Health	81.48 (18.04)	80.79 (17.07)	0.70	1.39	0.166
Notes: Two-sample t-test assuming equal variances. Mean difference is calculated as mean(BISP=0) − mean(BISP=1). Sample sizes: BISP=0 n=8,426, BISP=1 n=1,497 (total n=9,923).					

The aftermaths of the OLS regression model is presented in Table 4. Each column reports an OLS regression for a different outcome, with column (1) using the composite HHDI and columns (2)-(4) using the Living, Health, and Education sub-indices. In this setup, the BISP(=1) coefficient captures the average difference in the relevant index between BISP-recipient and non-recipient households, conditional on the model specification shown, with robust standard errors reported in parentheses. Model fit varies across outcomes. The Education model has the highest explanatory power (R-squared = 0.336), followed by HHDI (0.248), while Health (0.102) and especially Living (0.0895) are lower. All regressions use the same sample size (N = 9,923). These results should be read descriptively, since the BISP association may reflect selection or targeting differences rather than any programme effect until richer specifications are considered.

The estimated association is negative and statistically significant for three of the four outcomes. For the composite index, BISP receipt is associated with a 1.032-point lower HHDI (-1.032, SE 0.300), significant at the 1 per cent level of significance. For living standards, the gap is larger in magnitude: recipients are associated

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with a 2.722-point lower Living sub-index (-2.722, SE 0.510), also significant at the 1 per cent level. For education, the coefficient is -1.079 (SE 0.457), statistically significant at the 5 per cent level, indicating a smaller but still meaningful negative association. Health stands out as the only domain where the coefficient is positive (0.703, SE 0.483) and statistically indistinguishable from zero, suggesting no clear conditional mean difference in this sample.

In descriptive comparisons, lower living standards scores among BISP-recipient households are often consistent with targeting and selection, since recipients are typically drawn from households facing deeper material deprivation at baseline. The living-standards domain also tends to capture conditions that adjust slowly, such as housing quality, access to utilities, durable assets, energy arrangements, and crowding, which reflect longer-run constraints rather than short-run liquidity. As a result, even if households receive additional resources, their measured living conditions may remain lower on average when compared to non-recipients who start from a stronger position within the same broad income segment. Geographic and service-access constraints can reinforce this pattern: rural residence and local infrastructure gaps may limit the scope for observable improvements in housing and basic services, especially among poorer households. Since cross-sectional comparisons combine pre-existing differences with any subsequent changes, the observed gaps are best interpreted as compositional and associational, not as programme effects.

Lower education index scores among BISP-recipient households are consistent with targeting and selection, since recipients are likely drawn from households with deeper baseline educational disadvantage, including lower adult schooling and a weaker learning environment at home. Education indicators such as years of completed schooling, literacy, and sustained enrolment also move slowly because they reflect cumulative histories rather than short-term fluctuations, so any support received may not translate quickly into a higher index value in a cross-section. At the same time, educational progress is often shaped by constraints beyond household liquidity, including the availability and distance of schools, the opportunity cost of children’s time, and exposure to household shocks that disrupt attendance and progression. These factors can continue to suppress observed education outcomes even when financial pressure eases. Since cross-sectional comparisons combine pre-existing differences with any later changes, the observed recipient–non-recipient gap should be interpreted as a compositional, associational contrast rather than a programme effect.

The absence of a clear health index gap between BISP-recipient and non-recipient households can reflect the fact that, within the bottom segment, both groups often face broadly similar constraints in health service availability, travel distance, and perceived quality, so the index does not sharply distinguish households by receipt status. A health index can also be less discriminating in a cross-section if it relies on indicators with limited variation or outcomes that change slowly relative to education and living conditions. At the same time, offsetting dynamics may be at play: recipients could begin with weaker baseline health conditions, while modest financial breathing space may ease some access-related costs, producing similar average scores in a snapshot without implying convergence in underlying risk. Finally, health shocks and need-based care-seeking can blur group differences, since illness incidence and timing are not perfectly aligned with observable socio-economic characteristics, especially among households clustered in broadly comparable deprivation.

A lower composite HHDI score among BISP-recipient households is consistent with targeting and selection, since recipients are typically drawn from households facing deeper baseline deprivation even within the bottom segment. Because the index is composite, it aggregates multiple dimensions of household development, so persistent shortfalls in any one domain can pull down the overall score even when other components look broadly similar across groups. This matters particularly when the index includes indicators that are slow to change, such as education attainment and housing or asset-related living conditions, which tend to reflect cumulative histories and long-run constraints rather than short-run fluctuations. A cross-sectional snapshot therefore captures where households stand at a point in time, mixing pre-existing disadvantage with any later adjustments that may have occurred after receipt. For this reason, observed recipient-non-recipient gaps are best interpreted as compositional and associational differences that align with baseline deprivation, rather than as evidence of programme effects.

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Columns (1)-(4) relate to HHDI, Living, Health, and Education, and the reported coefficients should be read as conditional associations given the covariates included. The province indicators compare KPK, Punjab, and Sindh to an omitted reference province. Relative to that omitted province, KPK is positively associated with HHDI (5.103***, SE 0.401), Health (5.090***, SE 0.691), and Education (10.17***, SE 0.561), while its Living coefficient is close to zero and not statistically significant (0.0492, SE 0.648). Punjab shows a strong positive association with HHDI (9.623***, SE 0.358), Health (15.57***, SE 0.602), and Education (15.66***, SE 0.494), but a negative association with Living (−2.356***, SE 0.583). Sindh follows a similar domain-specific pattern: positive for HHDI (3.524***, SE 0.383), Health (10.24***, SE 0.661), and Education (2.735***, SE 0.523), yet negative for Living (−2.400***, SE 0.621). Urban residence, relative to rural, is consistently positive across outcomes, including HHDI (4.995***, SE 0.300), Living (5.556***, SE 0.462), Health (3.861***, SE 0.459), and Education (5.568***, SE 0.493). Taken together, the province coefficients suggest that geographic differences are not uniform across domains, with some regions scoring higher in health and education while not necessarily showing stronger living-standards values as captured by this index.

Household structure and head characteristics also display clear patterns. A higher dependency ratio is associated with lower HHDI (−0.0772***, SE 0.00511), lower Living (−0.204***, SE 0.00863), and lower Education (−0.0668***, SE 0.00821), alongside a positive association with Health (0.0394***, SE 0.00716). This sign reversal should be interpreted cautiously as an association that may reflect how the health index varies with household composition rather than “better health” per se. Male headship is negatively associated across all outcomes: HHDI (−3.414***, SE 0.436), Living (−4.555***, SE 0.742), Health (−1.485**, SE 0.606), and Education (−4.202***, SE 0.703). Head education is also negative and strongly significant for all outcomes, including HHDI (−8.327***, SE 0.226), Living (−5.099***, SE 0.362), Health (−1.554***, SE 0.358), and especially Education (−18.33***, SE 0.356); this unexpected direction could reflect variable coding choices (for example, higher values indicating lower schooling) or selection patterns within the sample rather than a structural relationship. Model fit differs by outcome (R^2 = 0.248 for HHDI, 0.0895 for Living, 0.102 for Health, and 0.336 for Education; N=9,923), suggesting the covariates account for more variation in education than in living standards or health. All of these patterns remain descriptive and may partly reflect compositional differences and measurement or coding of the controls.

Table 4: OLS model estimates on household development

	(1)	(2)	(3)	(4)
VARIABLES	HHDI	Living	Health	Education
BISP(=1)	-1.032***	-2.722***	0.703	-1.079**
	(0.300)	(0.510)	(0.483)	(0.457)
KPK(=1)	5.103***	0.0492	5.090***	10.17***
	(0.401)	(0.648)	(0.691)	(0.561)
Punjab(=1)	9.623***	-2.356***	15.57***	15.66***
	(0.358)	(0.583)	(0.602)	(0.494)
Sindh(=1)	3.524***	-2.400***	10.24***	2.735***
	(0.383)	(0.621)	(0.661)	(0.523)
Urban(=1)	4.995***	5.556***	3.861***	5.568***
	(0.300)	(0.462)	(0.459)	(0.493)
Dep. Ratio	-0.0772***	-0.204***	0.0394***	-0.0668***
	(0.00511)	(0.00863)	(0.00716)	(0.00821)
Head male(=1)	-3.414***	-4.555***	-1.485**	-4.202***
	(0.436)	(0.742)	(0.606)	(0.703)
Head Education(=1)	-8.327***	-5.099***	-1.554***	-18.33***
	(0.226)	(0.362)	(0.358)	(0.356)
Constant	64.42***	89.51***	70.75***	33.01***

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	(0.663)	(1.095)	(0.988)	(1.023)
Observations	9,923	9,923	9,923	9,923
R-squared	0.248	0.0895	0.102	0.336

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The estimates of the propensity score matching techniques with Kernel Density estimation is presented in Table 5. The use of PSM in studying the impact of policy intervention is robust because it helps to control for confounding variables that could influence both outcome and explanatory variables, causing a spurious association. PSM is featured with randomization – process of randomly allocating subjects to different treatment groups to ensure that each group is similar in all respects except for the treatment they receive.

Table 5 contrasts raw mean differences ("Unmatched") with matched comparisons reported as the ATT, where the treated group (BISP recipients) is compared to a reweighted control group designed to be closer on observed characteristics. The shift from Unmatched to ATT indicates how much of the initial gap is associated with observable differences between recipients and non-recipients. For HHDI, the Unmatched means are 57.000 for treated households versus 59.725 for controls (Diff −2.726, SE 0.344, T 7.93). After matching, the treated mean remains 57.000 while the matched control mean falls to 57.864, shrinking the difference to −0.864 (SE 0.322, T 2.68). Living standards show a smaller reduction: Unmatched treated and control means are 68.800 and 71.816 (Diff −3.016, SE 0.510, T 5.92), while the ATT comparison is 68.800 versus 71.14 (Diff −2.34, SE 0.533, T 4.39). Education narrows sharply from an Unmatched gap of −4.465 (treated 21.412; controls 25.877; SE 0.562; T 7.95) to an ATT gap of −0.998 (treated 21.412; controls 22.41; SE 0.523; T 1.91).

Across outcomes, the ATT results suggest that sizeable portions of the raw differences in HHDI and Education are absorbed once the control group is made more comparable on observables, though some negative gaps remain. For HHDI, the matched difference of −0.864 is notably smaller than the raw −2.726, indicating reduced separation after balancing. Living standards remain negative and relatively large even after matching (−2.34), implying that differences in this domain persist more strongly in the matched comparison. Health is distinctive: the Unmatched difference is slightly negative (−0.696; treated 80.787 vs controls 81.483; SE 0.502; T 1.39), but the ATT flips sign to a positive 0.747 (treated 80.787 vs controls 80.04; SE 0.503; T 1.48), suggesting no stable directional difference once matched. These are descriptive matched comparisons, and while matching narrows gaps on observed characteristics, it cannot rule out unobserved differences between recipients and non-recipients.

The raw difference before matching shows a statistically significant difference of 2.726, while after matching difference remain statistically significant and reduces to 0.864. The differences in the living standards and education outcomes of the treated and control groups remain statistically significant before and after matching. On contrary, the differences in outcome of health remain statistically insignificant before and after the matching. In a nutshell, the households in treatment group (BISP-recipients) has less development level than the control group.

Table 5: Estimates of the PSM

Outcome Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
HHDI	Unmatched	57.000	59.725	-2.726	0.344	7.93
	ATT	57.000	57.864	-0.864	0.322	2.68
Living	Unmatched	68.800	71.816	-3.016	0.51	5.92
	ATT	68.800	71.14	-2.34	0.533	4.39
Health	Unmatched	80.787	81.483	-0.696	0.502	1.39
	ATT	80.787	80.04	0.747	0.503	1.48
Education	Unmatched	21.412	25.877	-4.465	0.562	7.95
	ATT	21.412	22.41	-0.998	0.523	1.91

The figure 1 shows the distribution of estimated propensity scores for BISP recipients and non-recipients. Both

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groups share a noticeable overlap across the mid-range of propensity scores, which supports the common support assumption needed for matching. At the same time, the treated group is more concentrated at relatively higher propensity scores, indicating that receipt is not random and is patterned by observed characteristics used in the propensity model.

In the raw (unmatched) sample, figure 2 shows the treated and control density curves differ, showing imbalance in the propensity score distribution prior to matching. In the matched panel, the treated and control curves move much closer and largely overlap, indicating that matching improves comparability between groups on the estimated propensity score. This suggests the matched sample is better balanced on observed covariates summarized by the propensity score.

Figure 3 reports standardized bias for each covariate after matching. Most covariates lie close to zero, implying that matching reduces mean differences between treated and control groups on key observed characteristics. A few covariates still show residual imbalance, but the overall pattern suggests acceptable post-matching balance, supporting the use of the matched sample for comparing outcomes.

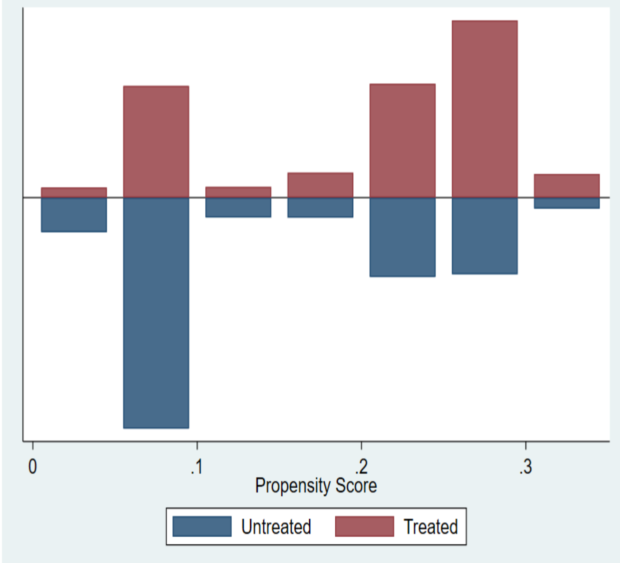

Figure 1. Propensity Score Distribution by Treatment Status (BISP Recipients vs Non-Recipients

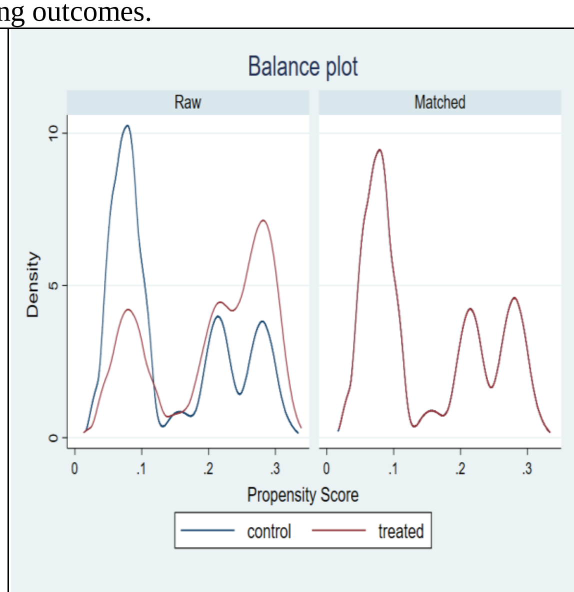

Figure 2. Propensity Score Balance Before and After Matching (Raw vs Matched Samples)

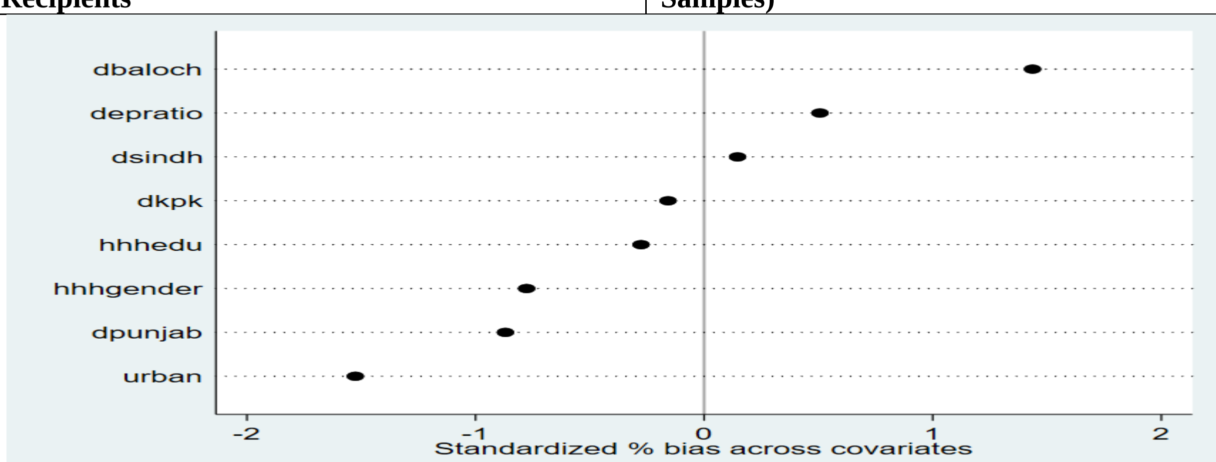

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Figure 3. Covariate Balance After Matching: Standardized Mean Differences Across Covariates

4. Conclusion

This study constructs a household-based human development index that combines living standards, health, and education outcomes for households in the bottom 40 per cent of the distribution. The composite HHDI adds a household-level lens that captures how multiple constraints cluster within the same household rather than treating development dimensions in isolation. Across raw comparisons, BISP-recipient households differ on average from non-recipients through lower composite HHDI scores, alongside lower living standards and weaker education profiles, while health differences are small and not statistically meaningful. In the OLS specifications with controls, the BISP indicator remains negatively associated with HHDI, living standards, and education, whereas the health association is not statistically distinguishable from zero. Matched comparisons further narrow the HHDI and education gaps relative to the unmatched differences, yet a negative separation persists for HHDI and living standards. Education differences become smaller and borderline, and the health comparison shows no stable separation, including a weak sign change.

Given that BISP-recipient households in the bottom 40 per cent are consistently observed with lower composite HHDI scores, driven mainly by weaker living standards and education profiles, the policy priority is to sharpen the programme's human development orientation without assuming these gaps are caused by receipt. Practically, this means using the HHDI sub-indices as a simple diagnostic to identify where recipient households remain most constrained and to sequence support accordingly: strengthen linkages that lower schooling discontinuity risks and improve sustained enrolment where education shortfalls are most visible, while addressing the living-standards constraints that appear persistent in both raw and matched comparisons. The absence of a clear separation in the health index suggests that health-related gaps may be less differentiating in this segment, so a targeted approach that focuses on households with the weakest health sub-index, rather than blanket expansion, is more defensible. Overall, the findings motivate a coordinated package across living standards and education, paired with routine monitoring of HHDI profiles among recipients to track whether observed deficits narrow over time.

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