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Social Protection Analysis on Labor Market of Pakistan

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Abstract

Social security is seen as a fundamental human right. The aim of this study is to explore the effect of social protection on the labor market dynamics. This study is based on the HIES dataset from 2018-19. Binary logistic regression is used to estimate the parameters of the labor force participation model. This study found that beneficiaries of social protection programs have a negative trend toward labor force participation in Pakistan. In addition, it is observed that some social indicators like age, rural residence, and male household head significantly affect labor force participation. This study also attempts to fill the gap by examining the effect of LFP on educational attainment. The study attempts to highlight the effect of social protection on LFP at the provincial level. The results explore the positive effect on labor force participation of beneficiaries by different age categories. Female labor force participation of grant recipients in Pakistan is still lower compared to males. The results show that the impacts of higher-educated people on the labor force are low compared to uneducated people. The study concludes by laying out some recommendations.

Keywords: Employment, Social Protection, Labor Force Participation, Social Indicator, Highest Education, Pakistan

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1. Introduction

Social protection encompasses social services, social safety nets and public works programmes designed to reduce economic insecurity and support vulnerable households (Mumtaz & Whiteford, 2017; Waqas & Awan, 2017). These interventions contribute to poverty reduction, improved health and nutrition, educational attainment, reduced child labour and the removal of barriers to women's employment (Afzal et al., 2019; Mumtaz & Whiteford, 2017). In Pakistan, the Government introduced the Benazir Income Support Programme (BISP) in 2008 to provide financial assistance to economically disadvantaged households and improve their living conditions (Waqas & Awan, 2017). Other major social assistance initiatives include the Zakat Programme and Pakistan Bait-ul-Mal (PBM), which provide different forms of financial and welfare support (Gazdar & Zuberi, 2014; Mumtaz & Whiteford, 2017). In addition, the country's social protection system includes the Provincial Employees Social Security Scheme (PESSI), Employees' Old-Age Benefits Institution (EOBI), Government Servants Pension Fund, Public Sector Benevolent Funds, Group Insurance, Workers' Welfare Fund and Workers' Children (Education) Ordinance. Although these programmes share the objective of improving socioeconomic welfare, their implications for household consumption, investment and labour market participation may differ according to programme design and beneficiaries' circumstances (Ambler & De Brauw, 2019; Alzúa et al., 2013).

Labour market participation remains an important economic challenge in Pakistan, particularly because employment opportunities differ across demographic and geographical groups. According to the Pakistan Bureau of Statistics, unemployment rates were 4.9% for men and 8.5% for women during 2017–2018 (Pakistan Employment Trend, 2018). Similarly, male labour force participation was approximately 81%, compared with only 22% for women during the same period (Pakistan Bureau of Statistics, 2017–2018). These differences indicate the importance of examining labour market outcomes in relation to gender-related circumstances, educational attainment, age and geographical location. Furthermore, social assistance may influence employment decisions by reducing immediate financial constraints or changing households' dependence on labour income. However, the direction of this relationship is unclear because transfer recipients face different employment opportunities and household responsibilities (Ambler & De Brauw, 2019; Alzúa et al., 2013).

Social protection also plays an important role in human capital development by reducing financial barriers to education. Educational attainment may improve employment opportunities, although its relationship with labour market participation varies across population groups and economic circumstances (Saavedra & García, 2012; Faridi et al., 2012). In Pakistan, educational qualifications are generally classified into matriculation, comprising ten years of schooling; intermediate education, comprising eleven to twelve years; and bachelor's and master's qualifications, representing approximately fourteen to sixteen years of education (Ministry of Finance, 2018). Within BISP, the Waseela-e-Taleem initiative provides educational assistance to disadvantaged households. Reported programme payments increased from Rs. 750 to Rs. 1,000 per quarter, while approximately 2.7 million children were reported to have enrolled during 2018–2019 (BISP, 28 August 2019). In addition to supporting educational participation, social transfers may facilitate consumption smoothing, savings and productive investment. Nevertheless, their relationship with employment outcomes depends on household characteristics, access to economic opportunities and the nature of the assistance provided (Mumtaz & Whiteford, 2017; Ambler & De Brauw, 2019).

1.1. BISP: An Introduction

The establishment of BISP in 2008 represented a major development in Pakistan's social protection system. The programme provides cash assistance to poor and vulnerable households to help meet essential consumption needs and reduce economic hardship (Mumtaz & Whiteford, 2017; Waqas & Awan, 2017). Government expenditure on social protection subsequently increased, with reported allocations of PKR 80 billion during 2019–2020 and a further PKR 120 billion during 2020–2021 (BISP, 2019). BISP primarily targets economically disadvantaged households, with women serving as the designated recipients of cash assistance (Tahir et al., 2018). In addition to direct financial support, associated initiatives have addressed education, entrepreneurship and vocational development. For example, Waseela-e-Haq offered soft loans of up to Rs. 300,000 to support small business activities (BISP, 10 October 2019), while Waseela-e-Rozgar provided technical and vocational training opportunities to selected household members (BISP Programme, 10 October 2019). These initiatives illustrate the different mechanisms through which social protection may relate to household welfare, human capital and economic participation.

Previous research has examined the relationship between social assistance and labour market outcomes, but the findings differ across programmes and national contexts. Ambler and De Brauw (2019) investigated

household labour supply under Pakistan's BISP programme, while Salehi-Isfahani and Mostafavi-Dehzooei (2018) examined cash transfers and labour supply in Iran. Similarly, Fruttero et al. (2020) investigated social programmes and formal employment in Brazil. These studies demonstrate that social transfers do not necessarily produce uniform labour market responses. However, differences in programme characteristics, beneficiary circumstances and labour market conditions complicate comparisons across studies. Therefore, examining employment-related differences among beneficiaries of different social assistance programmes can provide additional evidence about the characteristics associated with labour market participation in Pakistan.

Against this background, the present study investigates the relationship between social assistance programme type and reported labour market participation among beneficiaries in Pakistan, using the 2018–2019 Household Integrated Economic Survey (HIES). Specifically, the study addresses the following research question: How are social assistance programme type, demographic characteristics, educational attainment and provincial residence associated with reported labour market participation among social protection beneficiaries in Pakistan? To address this question, the analysis examines the association between BISP assistance and reported work activity relative to other social assistance programmes, while considering differences in age, household-head characteristics, educational attainment, rural–urban residence and provincial location.

The study contributes to the existing literature by examining these relationships through four binary logistic regression specifications using a common household survey dataset. In particular, it provides a comparative assessment of reported work participation among BISP beneficiaries and recipients of other assistance programmes, alongside educational, demographic and geographical differences. Unlike an evaluation comparing beneficiaries with non-beneficiaries, the analysis focuses on variation within the social assistance recipient population. Consequently, its findings describe conditional associations rather than the causal effects of receiving social protection. This distinction provides a more precise basis for interpreting the relationship between social assistance and labour market outcomes and may inform discussions about employment barriers and programme design in Pakistan.

2. Background of Literature

2.1. Social Transfers, Education and Labour Force Participation

Social protection programmes can influence educational attainment and labour force participation by reducing household financial constraints and supporting human capital development. Totouom et al. (2018) examined the relationship between education and female labour force participation in Cameroon, highlighting gender differences in employment outcomes across educational categories. Similarly, Yildirim and Dal (2016), using Turkey's 2011 Household Budget Survey, identified variations in labour force participation associated with social transfers, household composition and employment circumstances. In Pakistan, Sayeed (2014) examined social protection and educational participation using household survey evidence, suggesting that increased school enrolment may coincide with reduced labour market participation among younger individuals. However, lower participation associated with education should not necessarily be interpreted as an adverse employment outcome, particularly when schooling improves future employment opportunities (Totouom et al., 2018; Sayeed, 2014).

The relationship between social assistance and human capital development is also evident in Pakistan's social protection initiatives. BISP primarily provides financial assistance, whereas skills-oriented programmes seek to improve employability through vocational training. Therefore, the relationship between programme participation and employment may depend on the nature of assistance and beneficiaries' educational characteristics (Sayeed, 2014; Mumtaz & Whiteford, 2017). Similarly, Palaz et al. (2006) identified significant relationships between educational attainment and labour force participation in Turkey, while Faridi et al. (2012) examined the contribution of human capital formation to employment participation in Pakistan.

Evidence from developing countries further demonstrates the educational implications of cash transfers. Saavedra and García (2012), through a meta-analysis of conditional cash transfer programmes, reported improvements in educational outcomes, with variations across schooling levels and programme characteristics. Miller et al. (2009) examined Malawi's social cash transfer scheme and reported improvements in children's educational participation alongside reductions in child labour. Similarly, Chaudhury and Parajuli (2006) investigated the female school stipend programme in Punjab, Pakistan, identifying changes in school enrolment associated with financial assistance. These findings suggest that social transfers may support educational participation while influencing the allocation of household labour. Nevertheless, educational outcomes and

adult employment decisions represent distinct dimensions of social protection and should be evaluated separately.

2.2. Social Protection, Poverty Reduction and Economic Development

Social protection is widely recognised as an instrument for reducing poverty, improving household welfare and supporting economic security. Afzal et al. (2019) examined conditional and unconditional cash transfers in Pakistan, highlighting their implications for poverty reduction, education, healthcare and household empowerment. Similarly, evidence from developing countries indicates that programme design and household circumstances influence the relationship between income transfers and labour supply (Alzúa et al., 2013; Salehi-Isfahani & Mostafavi-Dehzooei, 2018).

In Pakistan, Mumtaz and Whiteford (2017) examined BISP's contribution to social welfare, reporting improvements in consumption, children's education and health-related outcomes. Ahmad et al. (2017), using evidence from two villages in Swat, also identified poverty-related benefits among programme recipients. Furthermore, Gazdar and Zuberi (2014) examined Pakistan's social protection arrangements, distinguishing BISP's focus on female beneficiaries from other forms of household assistance, including Pakistan Bait-ul-Mal. These studies demonstrate the importance of financial assistance in addressing household vulnerability; however, improvements in welfare do not necessarily indicate corresponding increases or decreases in labour force participation.

The broader relationship between social protection and economic development has also received considerable attention. Justino (2007), drawing on evidence from India, examined the contribution of social security to economic stability and sustainable development. Similarly, Waqas and Awan (2017) explored the relationships between social protection, gender and poverty, emphasising the importance of assistance programmes for disadvantaged populations. Although social protection may improve household welfare and reduce economic vulnerability, its relationship with employment depends on labour market conditions, beneficiary characteristics and the structure of assistance. Therefore, poverty reduction and labour market participation should be examined as related but analytically distinct outcomes.

2.3. Social Transfers, Labour Market Participation and Women's Empowerment

Empirical evidence concerning social transfers and labour market participation remains mixed. Fruttero et al. (2020), examining Brazil's Bolsa Família programme, identified positive associations between social assistance and formal employment among particular population groups. Similarly, Ambler and De Brauw (2019) investigated household labour supply under Pakistan's BISP programme, highlighting differences in employment patterns and working hours among household members. However, Salehi-Isfahani and Mostafavi-Dehzooei (2018), examining a large-scale cash transfer programme in Iran, reported heterogeneous labour supply responses across age groups and employment sectors. These findings suggest that financial assistance does not necessarily discourage employment and that its relationship with labour supply varies across economic and demographic contexts.

In Pakistan, ShuHong et al. (2017) examined existing social protection schemes, identifying implementation challenges involving programme accessibility, financial support and delivery mechanisms. Similarly, Tahir et al. (2018) investigated women's entrepreneurship and empowerment through BISP-supported activities, highlighting differences between individually managed enterprises and female–male partnerships. Their findings indicate that financial assistance may contribute to household income without necessarily producing equivalent improvements in women's social empowerment. Comparable evidence from India suggests that employment programmes can influence women's labour market participation and household bargaining power (Afridi et al., 2012). Furthermore, Akbulut (2016), using cross-country evidence, identified relationships between social transfers, gender disparities and labour force participation, suggesting that employment responses may differ between men and women.

Labour market outcomes also depend on structural employment conditions and household characteristics. Shah et al. (2015) examined employment challenges in Khyber Pakhtunkhwa, identifying labour market constraints associated with institutional coordination, employment networks and differences between labour demand and supply. Similarly, Alzúa et al. (2013), using experimental evidence from Mexico, Nicaragua and Honduras, examined the effects of welfare programmes on adult labour supply and reported variations across programme settings and household groups. These findings indicate that employment responses cannot be attributed

exclusively to financial assistance because local economic opportunities and programme design may also influence labour market behaviour (Afridi et al., 2012; Ambler & De Brauw, 2019).

Human capital and demographic characteristics provide further explanations for differences in employment participation. Faridi et al. (2012) identified positive relationships between human capital formation and labour force participation in Pakistan. Similarly, Ejaz (2011) examined female labour force participation, emphasising the importance of education, marital status, household responsibilities and employment opportunities. Borraz and González (2009), investigating Uruguay's conditional cash transfer programme, reported differences in child labour, schooling and women's working hours. Furthermore, Mastrobuoni (2009) examined the relationship between social security benefits and retirement-related labour supply decisions, while Gassmann and Trindade (2019) identified differences in employment behaviour between household heads and spouses receiving social transfers in the Kyrgyz Republic. Evidence concerning educational support also indicates that cash transfers may influence children's schooling and time allocation, thereby affecting household labour decisions (Miller et al., 2009; Saavedra & García, 2012).

The reviewed literature suggests that social transfers may reduce immediate financial constraints and facilitate education, training and employment-related activities. However, additional non-labour income may also influence individuals' willingness or ability to participate in available employment. These relationships vary according to gender, age, educational attainment, household responsibilities and regional economic conditions (Alzúa et al., 2013; Ambler & De Brauw, 2019; Gassmann & Trindade, 2019; Fruttero et al., 2020).

Although previous studies have examined social protection and labour supply, the findings demonstrate the importance of distinguishing programme types and beneficiary characteristics when interpreting employment outcomes. Accordingly, the present study extends this discussion by comparing reported labour market participation among BISP recipients and beneficiaries of other social assistance programmes in Pakistan, while examining demographic, educational and provincial differences using the 2018–2019 HIES dataset. This approach provides evidence on variations within the beneficiary population without assuming that observed associations represent causal programme effects.

3. Data

The analysis uses Pakistan's 2018–19 Household Integrated Economic Survey (HIES) data. The study focuses on respondents who reported receiving assistance under Pakistan's social protection programs. Further, the study developed four age categories (18-60). The study developed seven educational categories. The estimation sample contains 16,903 observations in the reported regression tables. The BISP indicator is coded 1 for BISP assistance and 0 for assistance from other programmes. Consequently, the coefficient on this indicator compares two types of assistance recipients; it cannot estimate the difference between receiving and not receiving social protection. The analysis is cross-sectional, and the manuscript does not provide sufficient information on the original sampling exclusions, missing-value treatment, or use of survey weights to determine whether estimates are nationally representative. These features should be considered when interpreting the reported associations. The four specifications retain the same reported number of observations, which facilitates comparison of the displayed estimates; however, the manuscript does not provide a sample-flow table or the underlying survey code needed to verify whether the estimation sample was constructed consistently across models. In addition, social programme receipt may be related to income, household vulnerability and programme eligibility, which creates a risk of selection bias in a cross-sectional comparison (Ambler & De Brauw, 2019; Mumtaz & Whiteford, 2017).

4. Methodology

4.1. Binary Logistic Regression

Binary logistic regression is appropriate when the dependent variable is binary. The current study employs a logit model. The logit model expresses the logarithm of the odds of the outcome as a function of explanatory variables. The logit model depends on the odds and the relative odds. Odds have a range from 0 to infinity. When the odds exceed 1, the occurrence is more likely to happen than not. When the odds are between 0.99 and 0, the occurrence is less likely to happen. The relative odds value shows the comparable association between two variables . The multivariable logit specifications include demographic, educational, and geographical covariates. The reported exponentiated coefficients represent adjusted odds ratios and should not be interpreted directly as changes in participation probabilities. An odds ratio below 1 indicates lower estimated odds relative to the stated reference category, holding the other included covariates constant. However, an estimated difference should not be described as established if its confidence interval includes 1 and its p-value

exceeds the conventional significance threshold. Given the observational design, the estimated coefficients describe associations and do not establish causal program effects.

The logit model is defined in general terms:

$Logit(P) = Log(P/(1-P))$

The general form of logistic regression is presented below. Its interpretation is based on the log odds of the observed binary outcome and the corresponding exponentiated coefficients.

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i$$

$$Y_i = \begin{cases} 1 & if\ Y_i > 0 \\ 0 & otherwise \end{cases}$$

To find the effect of social protection on the labor market, the following models are estimated.

- The econometric relationship between LFP and general indicators can be written as:

$$LFP\ \left[p\left(\frac{p}{1-p}\right)\right] = \alpha + \beta_1 AGE + \beta_2 BISP + \beta_3 HHHG + \beta_4 RG + \beta_5\, EDU + \mu \quad (4.1.1)$$

Equation (4.1.1) compares reported work participation and non-participation among social transfer recipients.

- The second model shows the effectiveness of the educational category in predicting labor force participation:

$$LFP\left[p\left(\frac{p}{1-p}\right)\right] = \alpha + \beta_1 AGE + \beta_2 BISP + \beta_3 HHHG + \beta_4 RG + \beta_5 Uneducated + \beta_6 Primary + \beta_7 Middle + \beta_8 Secondary + \beta_9 Intermediate + \beta_{10} Bachelor + \beta_{11} Masters/Above + \mu \quad (4.1.2)$$

Equation (4.1.2) shows the effect of educational categories on labor force participation or non-participation. In this model, education is converted into different educational categories.

- The third model shows the age categories in labor force participation:

$$LFP\left[p\left(\frac{p}{1-p}\right)\right] = \alpha + \beta_1 AgeX_i + \beta_2 BISP + \beta_3 HHHG + \beta_4 RG + \beta_5 Edu + \mu \quad (4.1.3)$$

Equation (4.1.3) shows the effect of age categories on the labor force participation of men and women. X_i represents the age *n* number of household members.

- The last model shows the province-wise impact on participation of the labor force:

$$LFP[p\left(\frac{p}{1-p}\right)] = \alpha + \beta_1 Age + \beta_2 BISP + \beta_3 HHHG + \beta_4 RG + \beta_5 Edu + \beta_6 Punjab + \beta_7 Sindh + \beta_8 KPK + \beta_9 Baluchistan + \mu \quad (4.1.4)$$

Equation (4.1.4) defines the provincial effect on labor force participation, or non-participation in the labor market. It shows labor force participation in all provinces of Pakistan. LFP indicates labor force participation, defined as whether an individual did or did not undertake any work for pay, profit, or family gain during the last month for at least one hour on any day. The variable takes a value of 1 if an individual is part of the labor force and 0 if they are not. Another variable, eED, is categorized as uneducated (value = 0); primary includes class 1, class 2, class 3, class 4, and class 5. The middle level includes class 6, class 7, and class 8, and the secondary includes class 9 and class 10. The intermediate level of education is based on a Polytechnic diploma, FA/F.SC/ I.Com. Bachelor's involves a BA/B.SC/ B.com/B.ED. Master/Above based on MA, MSc/M. ED, Degree in Engineering, Degree in Medicine, Degree in Agriculture, Degree in Law, M-Phil, and PhD. All these values indicate the educated category, which is coded as 1. The HHHD variable takes the value 1 if a participant is male and 0 if female. In addition, social transfer is coded as 1 if household members receive payment from BISP and 0 if they receive it from other programs. RG shows urban 1 and rural 0. Provinces show that the participants live in Khyber Pakhtunkhwa, Punjab, Sindh, and Balochistan.

A further measurement distinction is necessary. The survey question quoted above captures whether an individual performed work for pay, profit, or family gain for at least one hour. On its own, this describes work activity and does not include unemployed individuals who are seeking and available for work. Accordingly, check the variable's correspondence with the conventional definition of labor force participation against the HIES questionnaire and coding documentation. Until that check is completed, interpretations should remain closely tied to the reported binary work-status measure. Furthermore, the reference categories are uneducated

respondents for the education specification, ages 29–39 for the reported age indicators, and Punjab for the provincial specification, as suggested by the respective tables. Consequently, the dependent variable should be labelled consistently as the reported work-status measure wherever its operational definition is discussed. The equations and variable labels should also be checked against the original analytical specification before the findings are presented as definitive estimates.

5. Results and Discussion

Binary logistic regression was used to examine conditional associations between beneficiary characteristics, the type of reported assistance and the binary work-status outcome. Therefore, the reported estimates should be interpreted as associations rather than direct measures of programme effectiveness.

Table 1: Multivariable Logit Model for the Labor Force Participation

Variables	Logit Coefficients	Exponentiated Coefficients		Sig.	95% of C. I
	B	Exp (β)	St. Error		Lower-upper
Constant	-0.203	0.812	0.103	0.440	-
Age	0.018	1.018	0.001	0.000	1.015-1.021
BISP	-0.023	0.977	0.073	0.750	0.846-1.128
HHHG	0.418	1.520	0.084	0.000	1.290-1.790
RG	-0.547	0.578	0.033	0.000	0.541-0.618
EDU	-0.700	0.497	0.003	0.000	0.465-0.530
N	16903				
-2 log Likelihood	22513.073				
Cox and Snell R^2	0.050				
NagelkerkeR²	0.067				

Source: Author

Table 1 reports adjusted associations with the binary work-status outcome for 16,903 observations. Age is positively associated with the outcome (odds ratio [OR] = 1.018, $p < .001$), and the male household-head indicator is associated with higher odds (OR = 1.520, $p < .001$). The regional indicator has an OR of 0.578 ($p < .001$), which should be interpreted using the coding of urban = 1 and rural = 0. Education is also negatively associated with the outcome as currently coded (OR = 0.497, $p < .001$). However, the BISP indicator is not statistically significant (OR = 0.977, $p = .750$; 95% CI [0.846, 1.128]). Therefore, the estimates do not show that BISP receipt is associated with lower work participation than receipt of other social assistance after adjustment for the included covariates. The Nagelkerke pseudo-R^2 of 0.067 also indicates that the model has limited explanatory performance by this measure. In addition, the table title describes the model as bivariate, although it contains several explanatory variables and is therefore multivariable. The headings should distinguish logit coefficients, odds ratios, standard errors and confidence intervals to avoid confusion about the reported quantities.

Table 2: Multivariable Logit Model of Labor Force Participation by Educational Attainments

Variable	Logit coefficients	Exponentiated coefficients		Sig.	95% of C. I
	B	Exp (β)	St. Error		Lower-upper
Constant	-0.18	0.821	0.219	0.056	_
Age	0.018	1.018	0.002	0.000	1.015-1.021
BISP	-0.035	0.966	0.073	0.638	0.837-1.115
HHHG	0.433	1.541	0.084	0.000	1.308-1.817
RG	-0.585	0.557	0.034	0.000	0.521-0.596
Primary	-0.417	0.659	0.050	0.000	0.598-0.726
Middle	-0.888	0.412	0.057	0.000	0.368-0.460
Secondary	-0.706	0.494	0.052	0.000	0.446-0.547
Intermediate	-0.696	0.499	0.068	0.000	0.437-0.570
Bachelor	-0.863	0.422	0.081	0.000	0.360-0.494
Master & above	-1.205	0.300	0.098	0.000	0.247-0.363
N	16903				
-2 log Likelihood	22425.770				

Variable	Logit coefficients	Exponentiated coefficients		Sig.	95% of C. I
	B	Exp (β)	St. Error		Lower-upper
Cox and Snell R^2	0.055				
Nagelkerke R^2	0.073				

Source: Author

Table 2 introduces separate educational-attainment categories and retains 16,903 observations. Compared with the uneducated reference group, all reported categories have odds ratios below 1, including primary (OR = 0.659), secondary (OR = 0.494), bachelor's education (OR = 0.422) and master's education or above (OR = 0.300), with reported p-values below .001. However, these associations should not be interpreted as evidence that additional education reduces employment. Educational enrolment, age composition, family circumstances and differences between formal and informal work may affect the observed pattern. Similarly, the BISP contrast remains statistically insignificant (OR = 0.966, p = .638; 95% CI [0.837, 1.115]). Therefore, the results support a cautious interpretation of educational differences among assistance recipients rather than a causal claim regarding either education or BISP payments. Similarly, because the reference category is reported as respondents without formal education, the estimates describe differences from this group after adjustment for the included covariates; they do not demonstrate that educational attainment itself discourages employment. The absence of a statistically significant BISP difference remains consistent with Table 1.

Table 3: Multivariable Logit Model of Labor Force Participation by Age Level

Variables	Logit coefficients	Exponentiated coefficients		Sig.	95% of C. I
	B	Exp (β)	St. Error		Lower-upper
Constant	0.212	1.236	0.094	0.025	-
Age (18-28)	0.160	1.173	0.037	0.000	1.092-1.262
Age (40-50)	0.385	0.470	0.049	0.000	1.334-1.619
Age (51-60)	0.675	0.964	0.065	0.000	1.730-2.229
BISP	-0.022	0.978	0.073	0.759	0.847-1.129
HHHG	0.404	1.504	0.084	0.000	1.277-1.772
RG	-0.547	0.579	0.034	0.000	0.524-0.619
EDU	-0.693	0.500	0.033	0.000	0.462-0.534
N	16903				
-2 log Likelihood	22510.081				
Cox and Snell R^2	0.050				
Nagelkerke R^2	0.067				

Source: Author

Table 3 examines age-group differences while holding the other explanatory variables constant. The displayed estimates suggest higher odds for several age categories relative to the omitted reference age category. However, the table contains inconsistencies among the coefficients, exponentiated coefficients, and confidence intervals. Specifically, the coefficient of 0.385 for ages 40–50 implies an OR of approximately 1.470, whereas the printed OR is 0.470; likewise, the coefficient of 0.675 for ages 51–60 implies an OR of approximately 1.964, whereas the printed OR is 0.964. These numerical discrepancies require verification against the original output before interpreting the magnitude of the age effect. In addition, BISP remains statistically insignificant (OR = 0.978, p = .759; 95% CI [0.847, 1.129]). Therefore, the age pattern should be treated as provisional until the table is corrected. The confidence intervals presented for these age categories are compatible with the exponentiated positive coefficients, not with the printed odds ratios. Accordingly, the two printed odds ratios should not be treated as verified estimates until reconciled with the model output. The table's multivariable specification should also be identified accurately.

Table 4: Multivariable Logit Model of Labor Force Participation by Provinces

Variables	Logit Coefficients	Exponentiated coefficients		Sig.	95% of C. I
	B	Exp (β)	St. Error		Lower-upper
Constant	-0.024	0.976	0.108	0.823	-
Age	0.017	1.017	0.002	0.000	1.014-1.020
BISP	-0.029	0.972	0.074	0.700	0.840-1.124
HHHG	0.371	1.449	0.084	0.000	1.229-1.708
RG	-0.576	0.562	0.034	0.000	0.526-0.601
EDU	-0.704	0.447	0.034	0.000	0.447-0.510
Sindh	-0.227	0.797	0.039	0.000	0.738-0.859
KPK	0.233	1.262	0.046	0.000	1.153-1.382
Baluchistan	-0.351	0.704	0.056	0.000	0.631-0.786
N	16903				
-2 log Likelihood	22391.065				
Cox and Snell R2	0.057				
Nagelkerke R^2	0.076				

Source: Author

Table 4 adds provincial indicators with Punjab as the apparent reference province. The reported odds ratios are 0.797 for Sindh, 1.262 for Khyber Pakhtunkhwa, and 0.704 for Balochistan (each reported $p < .001$). These results suggest different work-status associations across provinces after adjustment for the listed characteristics. However, they should not be taken as evidence that provincial residence itself causes changes in employment, because unobserved labor demand, household composition, and local economic conditions may be relevant. The BISP coefficient is again not statistically significant (OR = 0.972, p = .700; 95% CI [0.840, 1.124]). Furthermore, the education coefficient and odds ratio in this table do not agree mathematically and should be verified. The Nagelkerke pseudo-R^2 is 0.076, which indicates limited model fit by that particular measure. Moreover, the printed education coefficient of -0.704 corresponds to an exponentiated coefficient of approximately 0.495, which differs from the displayed value of 0.447. This discrepancy should be resolved using the original statistical output, rather than changing either figure solely based on the manuscript.

5.1. Interpretation in Relation to Previous Evidence

The absence of a statistically significant BISP coefficient in all four specifications is important because it does not support a straightforward claim that BISP recipients participate less in work than recipients of other assistance programs. This finding should be interpreted alongside the mixed evidence from existing cash-transfer studies. For example, Ambler and De Brauw (2019) examine household labor supply within Pakistan's BISP program, while Alzúa et al. (2013) and Salehi-Isfahani and Mostafavi-Dehzooei (2018) examine labor-supply responses in different national settings. Furthermore, the demographic and provincial associations in this manuscript indicate that labor market participation cannot be evaluated independently of local opportunities and household circumstances. The evidence therefore aligns more with a heterogeneous labor market context than with a uniform employment-disincentive explanation. The reported finding is a lack of statistically detectable difference between BISP beneficiaries and recipients of other programmes, conditional on the model covariates. It is not evidence of equivalence between groups, nor does it establish that social protection has no effect on employment relative to receiving no assistance (Ambler & De Brauw, 2019; Salehi-Isfahani & Mostafavi-Dehzooei, 2018).

5.2. Robustness and Interpretation of Estimates

The reported models would be strengthened by presenting descriptive distributions of beneficiaries by age, gender, education, province, and program type; adjusted predicted probabilities or average marginal effects; and, where appropriate, survey-design-adjusted standard errors. In addition, model diagnostics and sensitivity checks would help establish whether the associations are stable across specifications. Separate male and female models and interactions between program receipt and provincial residence could examine heterogeneity if the original microdata and cell sizes permit. These are recommended analyses and are not presented here as completed empirical results. Furthermore, a transparent account of the eligibility criteria, the coding of the dependent variable and the selection of the comparison group would make the analysis easier to replicate. Where permitted by the survey design, the authors could also report weighted estimates and contrasts across

gender and province; however, these additional analyses require access to the original data and are not claimed as results of the current study.

6. Conclusion

This study examined the relationship between social protection and labour market participation in Pakistan using the 2018–2019 HIES dataset and binary logistic regression involving 16,903 observations. The findings revealed that BISP assistance had a negative but statistically insignificant association with reported work participation across all four models. However, age, education, household-head characteristics, and provincial residence showed significant associations. These findings highlight the importance of demographic and regional differences in labour market outcomes. Therefore, strengthening education, skills development and rural employment opportunities may complement social protection programmes.

6.1. Policy Implications

Social protection policies should be integrated with employment generation, vocational training and educational development. In addition, provincial disparities and barriers affecting women and educated job seekers require targeted policy attention. However, reducing the duration of financial assistance cannot be recommended solely on the basis of the present findings (Mumtaz & Whiteford, 2017; Ambler & De Brauw, 2019; Faridi et al., 2012; Ejaz, 2011).

6.2. Study Limitations and Future Research

The study is limited by its cross-sectional design, beneficiary-only sample and binary work-status measure, which restrict causal interpretation and generalisability. In addition, limited information on survey weighting, sampling procedures, and model diagnostics affects robustness assessment. Future studies should employ longitudinal or quasi-experimental approaches and examine gender-specific, educational and provincial differences to provide stronger evidence on social protection and labour market participation.

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