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Determinants of Income, Policy Awareness and Access among Agricultural Labourers and Cultivators in Mirzapur District, Uttar Pradesh: Is Gender a Crucial Factor?

Reshma Gupta[1], Swati Shastri[1], and Ankit Nagar[2]

ABSTRACT

This exploratory study examines the socioeconomic factors of agricultural income and gender disparities in policy awareness and access among agricultural labourers and cultivators in Mirzapur district, eastern Uttar Pradesh. Using Primary data from 240 respondents, OLS regression is estimated for Pooled, Agricultural Labourers, and Cultivators samples, alongside Composite indices and binary logistic regression for policy awareness and access. Gender, farm size, workdays, and supplementary income are major predictors of overall income. Female cultivators are significantly less likely to access Kisan Credit Card and Krishi Vigyan Kendra, underscoring information asymmetry and the need for gender-oriented interventions and the involvement of SHGs.

Keywords: Agricultural Income, Gender Disparities, Policy Awareness, Agricultural Labourers, Policy

JEL Code: Q12, J16, O13, Q18, R11

I

INTRODUCTION

The gender pay gap is a widely recognised indicator of income inequality in the labour market between women and men (ILO, 2020). It refers to the disparity between the median earnings of female and male workers (OECD, 2017). In India’s agricultural sector, approximately 33% of agricultural workers and 48% of self-employed cultivators are women, and nearly 80% of economically active women in rural areas depend on this sector (Government of India, 2023). Despite their contribution to this sector, substantial and ongoing gender income gaps remain evident. The female labour force participation rate (LFPR) in rural India increased from 24.6 per cent in 2017-18 to 41.5 per cent in 2022-23 (Government of India, 2024). However, women’s participation is still characterised by lower wages, limited access to land, and less involvement in formal agricultural institutions. The emergence of science and technology has shifted India’s agricultural sector from reliance to an export-oriented one. However, despite this recent progress, the belief remains that women are not a major contributor to this sector, which is one reason they continue to earn less than men in agriculture (England et al., 2007).

National wage data indicate that male agricultural labourers earned ₹264.05 per day, compared to ₹205.32 for female agricultural labourers in 2017, resulting in a 22.2 per cent lower pay for females (Sawhney, 2022). In Mirzapur district, daily wage rates were ₹297.65 for men and ₹254.87 for women in 2024-25 (Government of India,

[1]Department of Economics, Banasthali Vidyapith, Banasthali, Rajasthan - 304022
[2]Department of Economics, Doon University, Dehradun, Uttarakhand- 248012

2025). This within-task difference stands in stark contrast to the much larger disparity in total monthly wages observed across different occupational categories. This divergence illustrates occupational segregation, with women mainly employed in lower-paying jobs and limited land access restricting their involvement in higher-income cultivation.

Uttar Pradesh, the most populous state with an emphasis on agriculture, has a considerable number of landless female labourers (Kalpagam & Arunachalam, 2008). In 2015-16, eastern Uttar Pradesh, including Mirzapur, had the lowest agricultural growth rate in the state at 1.6 per cent and an average monthly income of ₹6,668 for agricultural households (Jose et al., 2022). Although various government programs aim to address gender inequalities in income, land rights, financial inclusion, and skills development, thereby improving access to information and market opportunities and increasing earning potential, it remains uncertain how well these initiatives reach informal agricultural workers in districts such as Mirzapur. Previous research shows that some policies empower women; however, there remains a significant gap in awareness and access to these regulations, with no gender-specific allocation.

This study addresses that gap through two interrelated questions: first, what is the extent of disparity in total income and the socioeconomic determinants of total income among agricultural labourers and cultivators in Mirzapur? What factors influence these worker's awareness and access to important government schemes?

II

THEORETICAL FRAMEWORK

2.1 Human Capital and Segmented Labour Market Theories

These theories explain that productivity and wages are affected by factors such as education, experience and skill. However, benefits depend upon segmented labour markets, gender, and societal identity (Mincer, 1974; Therond et al., 2017). In agriculture, out of the two segments, which are primary and secondary, the second one includes women with limited access to land, credit, and information, mostly employed as daily wage labourers (Doeringer & Piore, 1970; Morin, 2025). This segmentation results in different labour patterns and gender pay gaps, such as wage labourers compared to those involved in cultivation, leading to separate earnings for men and women (Li et al., 2024).

2.2 Statistical Discrimination and Information Asymmetry

These two theories emphasise the significance of adoption and the dissemination of agricultural innovation. It shows that awareness and information are essential links between policy formulation and its implementation on the ground level. Factors such as gender, caste, land, education, and local networks significantly influence who ultimately benefits from government policies, who trusts them, and who can navigate the necessary procedures (Adisa et al., 2024; Morin, 2025). Further, statistical discrimination occurs when extension trainers primarily interact with male cultivators, thereby widening the awareness gap (Phelps, 1972).

2.3 Resources-Agency-Achievements Framework

From an institutional perspective, formal policies such as credit, extension, price support, and social protection operate within a framework of existing norms, habits, and power dynamics (Kabeer, 2018; Lee & Wie, 2017; Pandoh & Singh, 2025). Therefore, access to government programs depends not only on eligibility but also on who controls land, information channels, and local networks (Viana & Waquil, 2022).

Synthesising these elements, this study focuses on two interconnected pathways.

1. Gender → land ownership & labour segment → Income
2. Socioeconomic position → Policy awareness → Policy access

These pathways enable the authors to select the explanatory variables in the income and policy models and frame the interpretation of gender differences in wages, awareness and access.

III

LITERATURE REVIEW

The literature indicates that socioeconomic factors, like gender, caste, education, and various agricultural tasks segregation, are consistently identified as main contributors to the gender pay gap (Aslam, 2009; Azad & Hari, 2024; Deshpande, 2000; Rani et al., 1990). Mishra & Singh (2019) found that almost 90 per cent of casual labourers in Uttar Pradesh belong to SC/ST or OBC categories, reflecting caste-based occupational sorting in the rural labour market. Returns to productive factors tend to increase with each additional year of age, resulting in higher wages for men than for women (Al-Samarrai, 2007). This gap probably arises from differences in experience, as men's experience typically accumulates more quickly. In contrast, women leave the workforce to care for children, thereby affecting their accumulated experience. Blau & Kahn (2017) found in their study that gains in work experience close the gender gap more effectively than increases in educational achievement, which supports the other studies. Goldin (2014) documented that, in the United States, within-occupation pay inequalities account for a larger share of the gender pay gap than disparities between occupations. This pattern has also been observed in India.

In India, Sengupta & Puri (2022) discussed the 'sticky floor' phenomenon using quantile regression, where women in the lowest income groups experience the highest relative discrimination. Gupta & Kothe (2024) confirmed through their decomposition analysis using NSS data that the unexplained discrimination component (37.9%) in Indian casual labour markets exceeds the part explained by endowments, which is only 3.1%. This indicates that employer undervaluation of women's work is the dominant mechanism, rather than skill gaps. Pattnaik et al. (2018) showed, across four census rounds (1981-2011), that the feminisation of agriculture in India indicates agrarian distress rather than empowerment, as women's growing participation in farm work increases their labour burden without leading to income equality.

Farm size and land tenure are established determinants of income in Indian agriculture. Agarwal et al. (2021) found that women own only 14 per cent of rural land across nine Indian states, and Das & Srivastava (2021) confirmed that land size is the dominant source of income inequality (Gini≈ 0.6) among agricultural households in India, a structural constraint that directly reduces women's participation in cultivation. Women who do not possess land encounter a fundamental income limit that cannot be overcome by wage policy alone.

Regarding policy awareness, Aditya et al. (2017) found that only 23.7 per cent of farmers were aware of the Minimum Support Price for kharif crops, and Agnihotri & H.R. (2022) reported lower awareness of women-oriented schemes among rural women than among men. SHG members significantly enhance both awareness and utilisation of government entitlement schemes when they are actively involved in the dissemination process in India (Kumar et al., 2019). Information mainly flows through institutions that male household members access more frequently, making social capital the primary obstacle to women's participation in schemes due to their mobility barriers (Coleman, 1988).

No previous research has studied income determinants and policy coverage within a unified framework for the rural agricultural sector in eastern Uttar Pradesh to understand the pay gap and the role of policy in that context. This primary data-based study addresses this gap by employing a three-model OLS approach and an eligibility-defined binary logistic regression to examine awareness and access to policies across two blocks in the Mirzapur district.

IV

METHODOLOGY

4.1 Study Area, Sample Size, and Sampling Design

The study is based on 240 respondents, selected through purposive and convenience sampling, using a semi-structured interview schedule from Mirzapur district, Uttar Pradesh. The data were collected on socio-economic factors, awareness, and access to the following policies, which are Sukanya Samriddhi Yojana (SSY), Minimum Support Price (MSP), Krishi Vigyan Kendra (KVK), Kisan Credit Card (KCC), and Mahila Shakti Kendra (MSK). The survey was conducted from October to December 2023, focusing on crop shifts, which helped the authors to observe changes in agricultural labourers' wages while collecting only recent wages to minimise recall bias. The two blocks, Kone and Sikhad, were selected purposively to account for the spatial variation of the pay gap between a block near the district headquarters and one located farther away. The sample included an equal number of male and female participants (Figure 1).

The authors have adopted convenience sampling, which is appropriate despite its limitations, in the absence of a comprehensive sampling frame for informal agricultural workers due to the seasonal and transient nature of agricultural employment. This method enabled them to leverage their understanding of the region's socio-economic and cultural context to engage effectively with both cultivators and agricultural labourers. The draft of the semi-structured schedule was reviewed by two academic experts specialised in rural development; their feedback helped refine the wording of sensitive questions about income and decision-making power. A pilot study was conducted with 20 participants from a nearby village to assess the content validity, logical flow, and duration of the questionnaire.

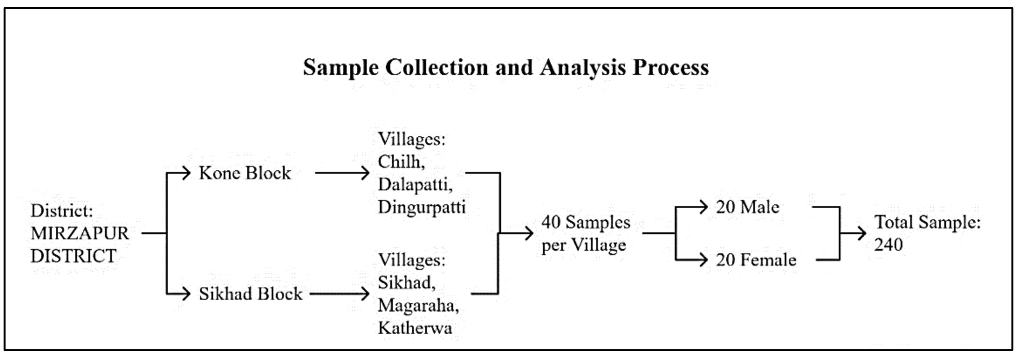

FIGURE 1. SAMPLE SELECTION FLOW CHART

4.2 Definition of Income Components

In the study, total income consists of farm income as the main source and other sources as a secondary. Farm income comprises wages earned by agricultural labourers working on others' land or income generated by cultivators from their own land. Income from other sources (IFOS) includes government welfare payments, pensions, and home-based activities such as carpet weaving and milk selling. For labourers, monthly income is calculated from daily wage rates and the average number of working days. For cultivators, it reflects the monthly equivalent of seasonal crop income as reported by respondents.

4.3 Model Specification

4.3.1 Model 1: Determinants of Total Income (Three-Model OLS Approach)

Three OLS models with robust standard errors are estimated using the natural logarithm of total income as the dependent variable. Square root transformations are applied to farm size and income from other sources to address distributional skewness. Model 1 (Pooled, n = 240) includes the overall sample with employment pattern as a control variable and an interaction term between employment pattern and farm size. Model 2 (Agricultural Labourers, n = 137) is estimated on the agricultural labourers sub-sample, excluding the employment pattern interaction term and retaining hours spent in the field. Model 3 includes categories both and cultivators (n=103). This three-model approach directly addresses a pooled model that conflates structurally distinct income-generating processes.

Model I (N=240)

ln(Total Income) = β0 + β1 Gender + β2 Age + β3 Social Group + β4 Education + β5 Farm
Size + β6 Employment Pattern + β7 IFOS + β8 Average Days Working + β9 (Employment Pattern × Farm Size) + ε

Model II (n=137)

ln(Total Income) = β0 + β1 Gender + β2 Age + β3 Social Group + β4 Education + β5 Farm Size + β6 IFOS + β7 Average Days Working + β8 Hours Spent in Field + ε

Model III (n=103)

ln(Total Income) = β0 + β1 Gender + β2 Age + β3 Social Group + β4 Education + β5 Farm Size + β6 Employment Pattern + β7 IFOS + β8 Average Days Working + ε

4.3.2 Model 2: Policy Awareness and Access

In this study, binary logistic regression models are estimated for awareness and access of six policy schemes across two eligibility-defined sub-samples. Agricultural productivity schemes (MSP, KCC, and KVK) are modelled among cultivators and workers engaged in both activities (n=103), who constitute the eligible population for cultivation-linked entitlements. Women's welfare schemes (MSK and SSY) are modelled among female respondents (n=120). Gender is excluded in category B since all respondents are female; employment pattern becomes the primary stratification variable. Sociological group is coded as SC/ST versus non-SC/ST in both categories. This eligibility-restricted design follows Nagar et al. (2021) & Parisi et al. (2023). They restricted awareness and access models to scheme-eligible respondents to ensure that no-access responses are substantively interpretable.

Awareness/Access of the policy: Yes=1, No=0

Category A

Logit (Aware/Access) = β0 + β1 Gender + β2 Age + β3 Social Group + β4 Education + β5 Farm Size + β6 Employment Pattern + β7 Total Income + ε

Category B

Logit (Aware/Access) = β0 + β1 Age + β2 Social Group + β3 Education + β4 Farm Size + β5 Employment Pattern + β6 Total Income + ε

An odds ratio greater (less) than 1 indicates higher (lower) odds of being aware of or accessing a scheme relative to the reference group, holding other variables constant.

V

RESULT AND DISCUSSION

5.1 Descriptive Statistics: Income and Gender Disparities

Table 1 presents a descriptive summary of average monthly total income and the income gap, disaggregated by gender, employment pattern, and block level. Overall, men earn a mean monthly income of ₹20,935, compared to ₹11,603 for women, resulting in a raw gender income gap of 44.6 per cent. The income gap is substantial among agricultural labourers (48.6 per cent), and 43.7 per cent among workers involved in both activities. Female cultivators report a higher average monthly income of ₹36,693 than male cultivators, at ₹30,253. This apparent reversal results from a group of seven female cultivators in block 1 (Dingurpatti village), who own quite large farms ranging from 1.01 to 1.52 hectares and reported monthly earnings between ₹71,600 and ₹1,13,400. Their presence substantially inflates the mean income of female cultivators. The underlying gender-income gap emerges as statistically significant and negative after controlling for farm size in the regression analysis. This pattern shows Simpson's Paradox, in which a confounding variable (farm size) reverses the apparent direct relationship between gender and income. The descriptive finding confirms the argument that land access is the primary determinant of income in the cultivation segment (Agarwal, 1994).

Block-level patterns show a clear divergence within block 1 (Kone). The gender income gap is minimal at 1.7 per cent, primarily due to high-earning female cultivators in Dingurpatti village. Conversely, in block 2 (Sikhad), a more remote area, the gap widens to 71.8 per cent. This suggests that geographic remoteness increases female income disadvantages by limiting market access and institutional support. The aggregate raw income gap of 48.6 per cent is much higher than the official daily wage difference for agricultural workers in Mirzapur. This disparity reflects factors such as occupational segregation, unequal land access, and differences in working days, which are structural issues that daily wage comparisons alone cannot fully capture.

TABLE 1. AVERAGE MONTHLY TOTAL INCOME BY GENDER, EMPLOYMENT PATTERN, AND BLOCK (N = 240)

Category	Female Mean (Rs)	Male Mean (Rs)	Gender Gap (%)
Overall	11,603	20,935	44.6
Agricultural Labourers	4,486	8,736	48.6
Cultivators	36,693	30,253	F > M *
Both-Activity Workers	16,604	25,946	36.0
Block 1 (Kone)	15,877	16,150	1.7
Block 2 (Sikhad)	7,328	25,987	71.8

5.2 OLS Regression: Determinants of Total Income

This study used linear regression to identify the significant contributors to the log of total income. The OLS regression for all three models demonstrates strong explanatory power, with R^2 values of 0.867, 0.816, and 0.870 (Table 2). The Breusch-Pagan test reveals no significant heteroskedasticity in any of the models ($p>0.10$). The Ramsey RESET test indicates omitted-variable bias in all three models, consistent with constraints of primary survey data in informal agricultural contexts, where social capital networks, seasonal income variation, and market access conditions cannot be fully quantified with structured interview instruments. The mean VIF values are within acceptable ranges for all three models. The higher value in the agricultural labourers model (8.37) indicates the unequal caste distribution in that sub-sample, which is dominated by SC/ST respondents.

TABLE 2. OLS REGRESSION RESULTS: DETERMINANTS OF LOG TOTAL INCOME (THREE MODELS)

Variable	Pooled (n = 240)	Labourers (n = 137)	Both + Cultivators (n = 103)
Gender: Female (Ref: Male)	-0.388*** (0.053)	-0.425*** (0.059)	-0.157** (0.069)
Age	-0.003 (0.002)	0.001 (0.003)	-4.79e-05 (0.004)
OBC (Ref: General)	-0.024 (0.244)	0.577*** (0.083)	0.046 (0.225)
SC/ST (Ref: General)	0.086 (0.247)	0.622*** (0.063)	0.100 (0.217)
Education (years)	-0.002 (0.006)	0.009** (0.005)	0.007(0.006)
Employment Pattern (Ref: Cultivator)			
(2) Agri. lab.	0.671*** (0.127)	—	—
(3) Both	0.581*** (0.154)	—	0.294*** (0.059)
FS (sqrt[3], hectares)	2.733*** (0.184)	-0.592 (0.779)	2.710*** (0.134)
IFOS (sqrt)	0.007*** (0.001)	0.011*** (0.001)	0.003*(0.002)
Average Days of Working	0.036*** (0.006)	0.069*** (0.005)	0.003(0.007)
Hours Spent in the Field	—	0.053(0.048)	—
Integration of Emp.pat.*FS			
Agri.lab. × FS (sqrt)	-4.176*** (1.136)	—	—
Both × FS (sqrt)	-0.379 (0.268)	—	—
Constant	7.368*** (0.300)	6.123*** (0.433)	8.071*** (0.280)
R^2	0.867	0.816	0.870
Breusch-Pagan (p-value)	0.104	0.201	0.829
Mean VIF	3.45	8.37	1.93

[3]Square root transformations are applied to farm size and income from other sources to address distributional skewness.

5.2.1 Gender

Gender is a statistically significant negative predictor of total income in all three models, indicating that the gender income gap persists even after accounting for farm size (FS), education, caste, employment pattern (Emp.pat.) and income from other sources (IFOS). In the pooled model, being female is associated with approximately 38.8 per cent lower income ($p < 0.01$). The sub-sample analysis highlights the structural nature of this gap. It is 42.5% for agricultural labourers (Agri.lab.) ($p < 0.01$), but only 15.7% for combined cultivators and both-activity workers with a 5% significance level. This pattern confirms the segmented labour market framework that women in the secondary wage labour segment experience a significantly larger income gap than those in the higher-income cultivation segment. Sengupta & Puri (2022) documented a comparable 'sticky floor' pattern for Indian labour markets, where gender gap is greatest at the bottom of the earnings distribution, precisely the casual wage labour segment studied here. The smaller but still significant gap among cultivators reflects market access barriers and lower crop sale prices faced by female cultivators, consistent with Agarwal's (1994) argument that land access is necessary but not sufficient to eliminate the gender income gap.

5.2.2 Caste, Education, Farm Size, Working Days, and Income from Other Sources

Caste is statistically significant only in the agricultural labourers model. OBC and SC/ST labourers earn 57.7 and 62.2 per cent more, respectively, than the reference General category (both $p < 0.01$). They constitute the dominant majority of agricultural labourers in Mirzapur and are more integrated into the local agricultural economy, as also reported by Sinha et al. (2018). In the cultivator's model, caste does not play a significant role in total income when accounting for other factors such as land size and employment patterns, suggesting that income is primarily influenced by asset endowments rather than the division of tasks by caste.

Education is significant only for agricultural labourers at a 5 per cent level, with each extra year of schooling associated with about 0.93 per cent higher income for labourers. In this sample, farm returns for cultivators are significantly affected by farm size at the 1 per cent level of significance but are unaffected by years of education. Increasing farm size from 0.1 to 0.4 hectares is associated with approximately 72 per cent higher cultivator income. Since female respondents usually possess about 0.04 hectares on average compared to male's approximately 0.20 hectares, this fivefold disparity in farm size leads to reduced farm income for females, aligning with Agarwal's (1994) fallback position mechanism.

Income from other sources is significant across all three models, with the highest coefficient in the agricultural labourers model ($p < 0.001$). This confirms that diversification through government transfers and additional home-based activities plays a significant economic role for marginal agricultural workers in the study area (Rahman & Mishra, 2020). Average days of work is a significant positive predictor for agricultural labourers ($p < 0.001$), but not for cultivators. This difference highlights that labourers earn wages daily through employment, while cultivators depend on seasonal crop yields that do not depend on the number of working days.

5.3 Policy Awareness and Access (Composite Index Analysis)

In Table 3, female cultivators and both activity workers are aware of approximately two out of three agricultural schemes, whereas males are aware of approximately three, reflecting a 25.3% of awareness gap. The access gap is slightly larger at 30.1 per cent for females, with access to an average of one scheme compared to two for males. The awareness-to-access conversion rate shows only moderate gender differences. This finding directly supports Kabeer (2018) framework, which asserts that the unequal distribution of information, as a resource, more significantly contributes to outcome inequalities rather than variations in agency. Kumar et al. (2019) also reached the same conclusion across five Indian states, finding that passive information campaigns alone are insufficient and active facilitation through SHG networks results in meaningful improvements in uptake.

TABLE 3. COMPOSITE POLICY AWARENESS AND ACCESS INDICES BY GENDER - CATEGORY A (N = 103)

Policy Names (1)	Group (2)	N (3)	Awareness (/3) (4)	Access (/3) (5)	Awareness-to-Access Conversion (6)
MSP, KCC, KVK	Female	34	2.21	1.65	74.7%
	Male	69	2.96	2.36	79.9%
		103	25.3% (F lower)	30.1% (F lower)	-

Table 4 reveals a more distinct occupational divide among females. Female labourers are aware of fewer than one scheme on average and have limited access, scoring just 0.42 out of two for awareness and only 0.16 for access, which is less than half that of the cultivators. The study finds that the group that needs the most welfare support receives it the least.

TABLE 4. COMPOSITE POLICY AWARENESS AND ACCESS INDICES BY EMPLOYMENT PATTERN - CATEGORY B

Policy Names (1)	Group (2)	N (3)	Awareness (/2) (4)	Access (/2) (5)	Awareness to Access Conversion (6)
MSK, SSY	Cultivators	22	1.00	0.41	41.0%
	Agri.lab.	86	0.42	0.16	38.9%
	Both-Activity	12	0.50	0.50	100.0%

5.4 Binary Logistic Regression: Determinants of Awareness and Access of Policies

Policy awareness and access are analysed using two separate frameworks that reflect the scheme-specific eligibility criteria. Category A, related to agricultural productivity schemes such as Minimum Support Price (MSP), Kisan Credit Card (KCC), and Krishi Vigyan Kendra (KVK), is modelled among cultivators and both-activity workers ($n = 103$). In contrast, Category B, which pertains to women's welfare schemes like Mahila Shakti Kendra (MSK) and Sukanya Samriddhi Yojana (SSY), is modelled exclusively among female respondents ($n = 120$). The social group is categorised as SC/ST versus non-SC/ST in both categories after merging the nearly empty General reference group. All models exhibit strong discriminatory power and pass the Hosmer-Lemeshow goodness-of-fit test at the standard significance level. Additionally, the linktest hatsq is not significant in any model, indicating that the functional form is correctly specified throughout.

5.4.1 Category A: Agricultural Productivity Schemes (n = 103)

KCC and KVK

The findings show that female cultivators face substantially lower odds of KCC access (OR = 0.157, $p < 0.05$) and KVK access (OR = 0.17, $p < 0.01$) than male cultivators with similar farm size, education, and income (Table 5). Awareness of KCC is considerably lower among females (OR = 0.356, $p < 0.05$), while awareness of KVK does not show this disparity. This suggests that the main obstacle for KVK is access, rather than a lack of information among the respondents. Cultivators from the SC/ST social group encounter an increasing disadvantage in KCC. Their awareness (OR = 0.407, $p < 0.10$) and access (OR = 0.127, $p < 0.01$) are markedly lower than those of non-SC/ST cultivators. This aligns with Munshi's (2019) caste-as-network mechanism, which suggests that KCC relies on bank relationships where SC/ST social capital is weakest. Log income is a strong predictor of KVK awareness (OR = 5.147, $p < 0.01$), indicating that wealthier farmers are more engaged with extension services.

These findings clearly connect the OLS income gap to policy exclusion. Female cultivators who lack access to KCC credit and KVK extension services cannot finance inputs or adopt improved practices, further entrenching structural income disparities on the supply side.

MSP

Gender strongly and positively predicts access to the MSP scheme. Female cultivators outperform males at the access stage because MSP is implemented through post-harvest crop procurement, a process in which females directly interact when delivering produce to collection points. The exception proves the fact that women participate when a scheme's delivery channel is accessible to them. Education significantly improves MSP access (OR = 1.43, $p < 0.01$), highlighting functional literacy as a key prerequisite for managing government procurement. Farm size yields extreme odd ratios in both MSP models (27.86 and 102.3), reflecting quasi-complete separation, but the overall direction remains clear and anticipated, aligning with King & Zeng (2001).

TABLE 5. KEY LOGISTIC REGRESSION RESULTS (CATEGORY A - AGRICULTURAL PRODUCTIVITY SCHEMES)

Awareness (Dependent Variable)	AWARE_MSP (1)	ACCESS_MSP (2)	AWARE_KCC (3)	ACCESS_KCC (4)	AWARE_KVK (5)	ACCESS_KVK (6)
Gender Female (Ref. = Male)	.644 (.362)	5.34*** (3.287)	.356**(.188)	.157** (.122)	.451 (.251)	.17*** (.113)
Age	1.039* (.023)	1.052* (.028)	.994 (.025)	1.018 (.034)	.98 (.027)	1.023 (.03)
Social group- SC/ST (Ref.= Non-SC/ST)	1.804 (.952)	3.198* (2.08)	.407* (.2)	.127*** (.091)	2.44 (1.504)	1.043 (.633)
Education	1.096* (.057)	1.43*** (.146)	1.021(.052)	.961 (.056)	1.068 (.054)	1.045 (.058)
Farm Size	27.86** (39.3)	102.25***(168.95)	1.585 (1.775)	1.535 (2.685)	.69 (1.051)	5.584 (7.33)
Emp.Pat. Both-Activity (Ref. = Cultivators)	1.319 (.672)	3.52* (2.486)	1.117 (.554)	2.782 (1.971)	.606 (.318)	1.515 (.883)
Logtin	0.804 (.496)	.805 (.533)	1.333 (.691)	4.125 (3.577)	5.147*** (2.843)	2.966* (1.703)
_cons	0.124 (.726)	0 (.001)	.143(.672)	0* (0)	0*** (0)	0** (0)
Observations	103	103	103	103	103	103
Pseudo R^2	.218	.359	.145	.423	.266	.377
goodness of fit (p-value)	0.437	0.402	0.295	0.840	0.111	0.344
AUC	0.784	0.881	0.756	0.901	0.823	0.888
Link test (_hatsq)	0.808	0.333	0.515	0.231	0.276	0.218

TABLE 6. KEY LOGISTIC REGRESSION RESULTS (CATEGORY B -WOMEN-ORIENTED SCHEMES)

Awareness (D.V.)	AWARE_MSK	ACCESS_MSK	AWARE_SSY	ACCESS_SSY
Age	.967 (.025)	.935** (.027)	.943*** (.019)	.979 (.024)
Social Group SC/ST (Ref. = Non-SC/ST)	2.1 (1.23)	3.162 (2.347)	1.892 (.89)	3.408 (2.882)
Education	1.071 (.06)	1.085 (.068)	1.115** (.049)	1.158** (.066)
Farm Size	.464 (.726)	.235 (.439)	12.997** (15.008)	.004*** (.006)
2-Emp.Pat.(Agri.lab.) (Ref.= Cultivators)	.183** (.134)	.206* (.182)	.383* (.222)	.532 (.508)
3.Emp.Pat. (Both) (Ref.= Cultivators)	.236 (.229)	.589 (.6)	.788 (.641)	1.692 (1.569)
Logtin	1.871 (1.146)	2.708 (2.278)	.519* (.203)	3.979** (2.65)
_cons	.006 (.036)	0 (.002)	1433.526**(5042.398)	0** (0)
Observations	120	120	120	120
Pseudo R^2	.172	.22	.154	.186
goodness of fit (p-value)	0.1655	0.1185	0.5937	0.4108
AUC	0.741	0.768	0.732	0.769
Link test (_hatsq)	0.300	0.239	0.416	0.393

5.4.2 Category B: Women's Welfare Schemes (n = 120, females only)

Among the female sub-sample, agricultural labourers have about 82 per cent lower odds of being aware of MSK (OR = 0.183, $p < 0.05$) and 79 per cent lower odds of accessing it (OR = 0.206, $p < 0.10$) than cultivators (Table 6). The same pattern is reinforced for the awareness of the scheme SSY (OR = 0.383, $p < 0.10$). Each additional year is associated with about 5-6 per cent lower odds of awareness (OR = 0.943, $p < 0.01$), suggesting awareness of schemes declines with age.

A higher log of total income strongly increases the odds of accessing the SSY scheme (OR = 3.979, $p < 0.05$), but it does not significantly affect SSY awareness. SSY requires regular monthly deposits for 15 years, a financial contract that female agricultural labourers with low income cannot maintain, despite their awareness. Bhattacharya et al. (2020) identified this inflexibility in SSY's deposit as its primary implementation failure. Education improves both SSY awareness (OR = 1.115, $p < 0.05$) and access (OR = 1.158, $p < 0.05$). Women from group SC/ST show significantly higher SSY awareness than non-SC/ST women (OR = 1.892, $p < 0.05$), attributable to SHGs outreach, which has been more consistent in reaching these communities compared to others. Farm size here, too, results in contradictory extreme odds ratios in both SSY models (12.997 for awareness, 0.004 for access), indicating quasi-complete separation. These extreme odds ratios are interpreted cautiously as a statistical artefact of quasi-complete separation rather than a precise effect size.

VI

CONCLUSIONS AND POLICY IMPLICATIONS

This study finds that gender plays a crucial role in determining income, policy awareness, and access among agricultural workers in Mirzapur district. It is a fundamental structural factor that influences all three analytical dimensions. It affects the outcome by focusing on employment patterns, limited land ownership, and institutional barriers, rather than just explicit wage discrimination in task segmentation. Although several equal remuneration acts have been implemented, their enforcement at the ground level remains a challenge; strengthening the enforcement of these equal pay provisions is essential to reducing the gender-based pay gap.

The three-model OLS analysis is the study's central empirical contribution. The gender pay gap is 42.5 per cent for agricultural labourers and only 15.7 per cent for cultivators. Education is an important factor in determining agricultural labourers' income. Farm size is the dominant income determinant for cultivators, confirming the fallback position argument by Agarwal (1994). The fivefold disparity in land size between male and female respondents (0.20 versus 0.04 hectares) is the primary structural factor contributing to the income gap among cultivators. For agricultural labourers, the main predictors are the number of working days and their income. The structural differences among occupational groups have clear policy implications. A single wage-equalisation policy would not be effective for both, since their income-generating processes are fundamentally different.

The policy analysis shows that female cultivators score 25.3 per cent lower than males on agricultural scheme awareness and 30.1 per cent lower on access. Within the female sub-population, agricultural labourers score only 0.42 out of two on awareness of the women's welfare scheme, compared with one for cultivators. Across both groups, awareness to access conversion rates is broadly similar, which confirms that information asymmetry is the binding constraint, not procedural barriers. Access to KCC is 14.7 per cent for female cultivators, whereas it is 50.7 per cent for male cultivators. Similarly, KVK access stands at 29.4 per cent for females and 66.7 per cent for males. The regression confirms that, conditional on covariates, females' odds of access are much lower (KCC OR = 0.16; KVK OR = 0.17). The schemes with the largest gender awareness gaps, KVK and KCC, are exactly those most important for boosting agricultural income, reinforcing the structural disadvantage. In several logistic regressions across both categories A and B, the estimated constant term is nearly zero and statistically significant. This indicates a very low baseline probability of awareness or access when all covariates are set to their reference categories or to zero, which does not affect the main result.

There are some suggestions to strengthen the income and access gap in rural areas of Mirzapur district. Education is a crucial factor for agricultural labourers, particularly for females. Policies should focus on targeted skill enhancement programs for them. These should be implemented through existing local platforms, such as SHGs and Anganwadi centres, to address time and mobility constraints. Kumar et al. (2019) confirmed that SHG membership improves both awareness and uptake of entitlement schemes in India, but only through deliberate external outreach; therefore, SHG networks should be formally engaged as delivery channels for KVK and KCC outreach. The gap between awareness and access to SSY, where 33.6 per cent of women knew about it but only 14.2 per cent were able to access the scheme, reveals a procedural bottleneck. Field observations revealed that women who opened SSY accounts stopped making deposits because they did not understand the monthly deposit process and struggled to maintain it amid seasonal income fluctuations. Implementing a grace period, along with a targeted reminder system, through post office common service centres, can effectively resolve this issue. Land rights formalisation should be considered as a key income strategy. Implementing joint land registration, streamlining inheritance procedures, and conducting land rights awareness campaigns at the Panchayat level could serve as effective measures to reduce the land gap.

Limitations and Future Research: This study uses convenience sampling with a cross-sectional design, which limits the generalisability of the findings beyond the study villages and precludes causal conclusions; therefore, a further time-series study is recommended to examine the effects of the variables, as income is seasonally adjusted. The logistic models show quasi-complete separation for certain variables, such as farm size. To resolve this, Firth's penalised logistic regression could be used in future studies. Additionally, adopting a longitudinal approach to track changes in awareness and access following targeted outreach would provide more robust evidence for programme assessment.

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