INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
IFPRI

PROJECT NOTE DECEMBER 2025

Labor Market and Gender Impacts of Agricultural Mechanization: Evidence from Bangladesh's Combine Harvester Subsidy Program

Moogdho M. Mahzab, M. Mehrab Bakhtiar, Md Aminul Karim, Agnes Quisumbing, Shalini Roy

Summary

- Bangladesh's Phase III agricultural mechanization subsidy program (2020–2024) distributed over 35,000 machines worth BDT 1,595 crore (USD 163 million), including nearly 9,000 combine harvesters (CHs) that accounted for 84% of machinery expenditure.
- Earlier causal econometric analysis suggests that high-allocation CH areas saw 6-13% yield gains, 38-70% lower labor costs, and 12-26% lower production costs.
- In this note, we explore the distributional consequences of subsidized combine harvesters, particularly along gender lines.
- As a result of the program, self-employment in agriculture increases by 5.3 percentage points; men shift from wage labor to own-account farm work linked to mechanized operations.
- Female self-employment in agriculture declines by 2.6 percentage points; overall female employment probability falls by 1.8 percentage points.
- Unlike men, women do not transition into non-agricultural employment, indicating limited capacity to absorb displaced female workers.
- Among those who remain self-employed, women increase their time allocation substantially—suggesting that while fewer women participate, those who do work more hours, likely in livestock and fisheries.
- Foreign migration increases by 6.1 percentage points in high-mechanization areas, suggesting households use freed labor for overseas opportunities.

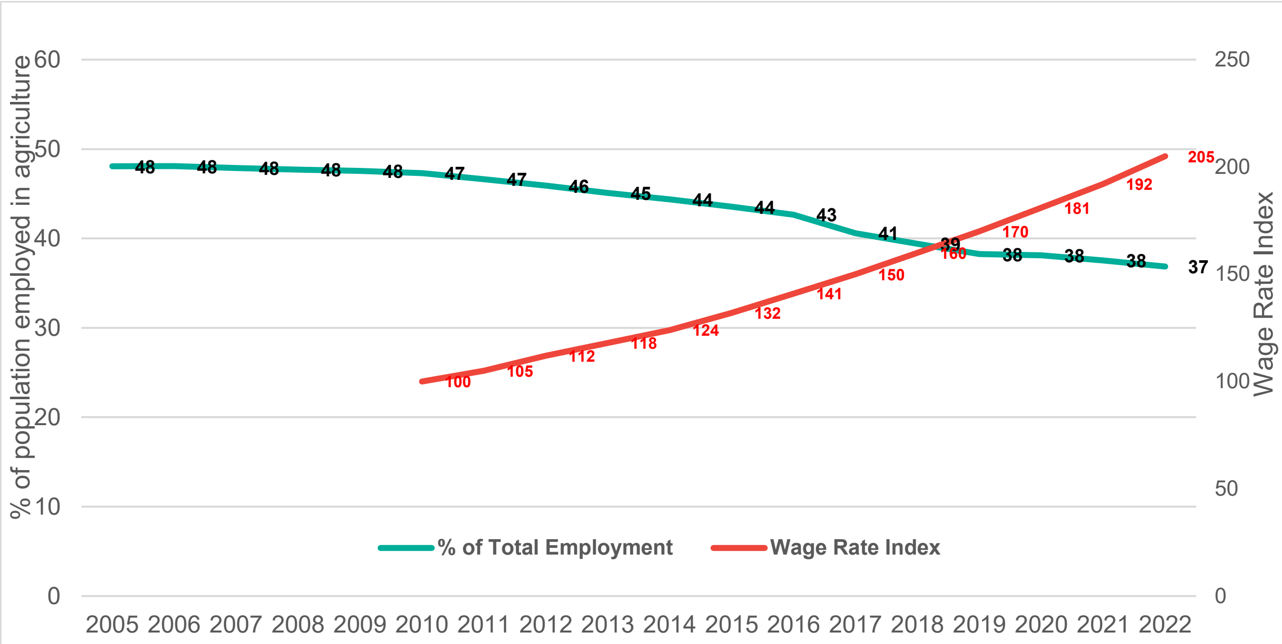
Introduction

Agricultural mechanization is widely seen as a critical driver of productivity growth and structural transformation in developing economies. Yet the benefits of mechanization are not gender-neutral: labor-saving technologies can displace women from traditional agricultural tasks while creating new opportunities that disproportionately favor men (Afridi et al. 2023). Recent evidence shows that Bangladesh has achieved a higher level of mechanization in tillage, irrigation, and threshing over the past decades and more recently in harvesting (Bakhtiar et al. 2025; Karim et al. 2024; Rahman et al. 2021), and at the same time, labor force dynamics in agriculture are also changing with a declining labor force and rapid increases in real wages (see Figure 1). Understanding how these shifts affect men and women differently is critical for designing inclusive agricultural policies.

Several recent studies have expanded our understanding of mechanization's impact on Bangladesh's agricultural sector. For instance, Vortia et al. (2021) found that the adoption of power tillers and tractors significantly increased rice productivity in Bangladesh. Similarly, Karim et al. (2024) found that mechanization in rice cultivation was associated with higher yields and reduced demand for hired and family labor. Recent studies by Bakhtiar et al. (2025), Ahammad et al. (2025) and Sujan et al. (2025) on combine harvester adoption in Bangladesh highlight that the use of harvesters can significantly improve yields and profitability while reducing labor time in rice production. However, the evidence remains limited on labor market dynamics of mechanization in Bangladesh.

Globally, the relationship between agricultural mechanization and labor market dynamics has been explored by some recent studies (Ma et al. 2024; Zou and Mishra 2024; Meng et al. 2024; Zheng et al. 2022 in China; Afridi et al. 2023 and Caunedo and Kala 2022 in India; and Belton et al. 2024 in Myanmar). However, one key aspect that remains relatively underexplored is the reallocation of time between different types of work and leisure that occurs when farm households adopt labor-saving technologies. As mechanization reduces the demand for manual labor, households must decide how to allocate the resulting "saved time." Do they use this time for off-farm income generation, leisure, education, or unpaid domestic care work? Are these decisions gendered, or do they depend on landholding size and household composition?

Figure 1: % of labor force employed in agriculture (2005-2022) and index of real agricultural wages (2010-2022)



Source: World Bank Indicators, various years & BBS Wage Rate Index (Base 2010-11)

This note addresses these gaps by examining how the adoption of combine harvesters (CHs)—a technology heavily promoted through recent government investment—reshapes rural labor markets in Bangladesh, with a particular focus on gendered outcomes. We analyze household participation in agricultural and non-agricultural work, gender-differentiated employment adjustments, and migration responses. Our central finding is that mechanization produces sharply divergent outcomes for men and women: men benefit from expanded self-employment opportunities possibly linked to mechanized operations, while women experience displacement from agricultural work with limited alternative pathways. Mechanization also reduces overall wage labor employment in agriculture and increases foreign migration. Together, the findings reveal how labor-saving agricultural technologies can unintentionally widen gender gaps in rural labor markets when implemented without complementary gender-sensitive interventions.

Policy Context and Motivation

Bangladesh's agricultural sector faces a confluence of structural challenges that threaten its long-term sustainability and food security objectives. Wages in agriculture increased by 30% in real terms between 2011 and 2018 (Karim et al. 2024), while seasonal labor shortages during peak harvesting periods have intensified due to rural-urban migration and competing employment opportunities in the non-farm sector. Labor market dynamics, combined with the imperative to feed a growing population, have positioned agricultural mechanization as a critical policy priority for Bangladesh (Bakhtiar et al 2025).

The Government of Bangladesh (GoB) launched Phase III of its mechanization support program in 2020, building on almost two decades of subsidy-driven policies to promote agricultural mechanization. This latest phase, with a budget of BDT 3,105 crore (USD 341 million), represents the country's most fiscally ambitious attempt to modernize agriculture through technological adoption. The program offered 50-70% purchase incentives for agricultural equipment ranging from small (seeders/bed-planters, threshers, diggers, and sprayers, among others) to large (combine harvesters).

In this phase, the GoB prioritized harvesting mechanization, recognizing it as the most labor-intensive agricultural operation and a critical bottleneck in the production cycle. This focus responded to acute labor shortages and high labor wages during harvest seasons, particularly in Haor (wetland areas) and coastal regions vulnerable to flash floods and climatic extremes. According to administrative data from the Department of Agricultural Extension (DAE), the program distributed over 35,000 subsidized machines between 2020 and mid-2023, including nearly 9,000 combine harvesters, representing a fiscal investment exceeding BDT 1,595 crore (approximately USD 163 million). This was 85% of the machinery purchase budget and nearly half of the total project budget.

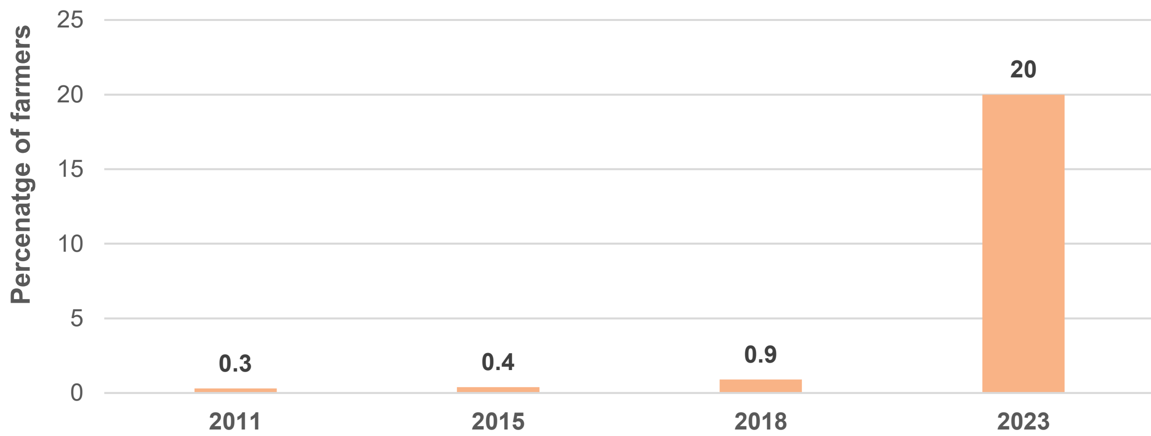
Table 1: Machine allocation under the subsidy program

Machine Type	Quantity	Tk (in crore)	% of Quantity	% of Expenditure
Combine Harvester	**8,912**	**1,595**	**25**	**84**
Seeder/Bed planter	12,059	137	34	7
Power Thresher	9,057	101	26	5
Reaper	2,327	28	7	1
Rice Transplanter	371	13	1	0.6
Others	2,621	20	7	0.01
Total	35,347	1894	100	100

Source: Authors' calculation using DAE's machine allocation data from 2022-2023 illustrates the evolution of mechanized harvesting in boro[1] rice production between 2011 and 2023. While mechanized harvesting remained below 1% in 2018, it jumped sharply to approximately 20% in 2023. This rapid increase in mechanized harvesting can be attributed to the Phase III subsidy program's strategic prioritization of CHs, with approximately 9,000 units distributed nationally between 2020 and 2023(See Figure 3).

[1] Boro is the dry season paddy in Bangladesh and is the most important and single largest crop in Bangladesh in respect of volume of production.

Figure 2: Trends in mechanized harvesting among boro rice farmers (2011–2023)



Source: Authors' calculations using BIHS 2011/12, 2015, 2018/19, and BIHS/SPIA 2024 data.
Note: Percentages reflect households that used mechanized planting or harvesting on at least one plot.

A recent assessment of the Phase III program by Bakhtiar et al. (2025) provides comprehensive evidence on program implementation and impacts. Drawing on administrative data, a survey of 979 Machinery Service Providers (including 400 CH MSPs), panel data from over 2,000 Boro rice-producing households, and 128 qualitative interviews, the report documents substantial program reach and strong productivity impacts. Causal econometric analysis suggests that high-allocation areas saw 6-13% yield gains, 38-70% lower labor costs, and 12-26% lower production costs. However, while these aggregate productivity gains were well-documented, the distributional consequences—particularly along gender lines—remain underexplored. This note extends that analysis by examining how mechanization reshapes labor markets differently for men and women.

Methodology

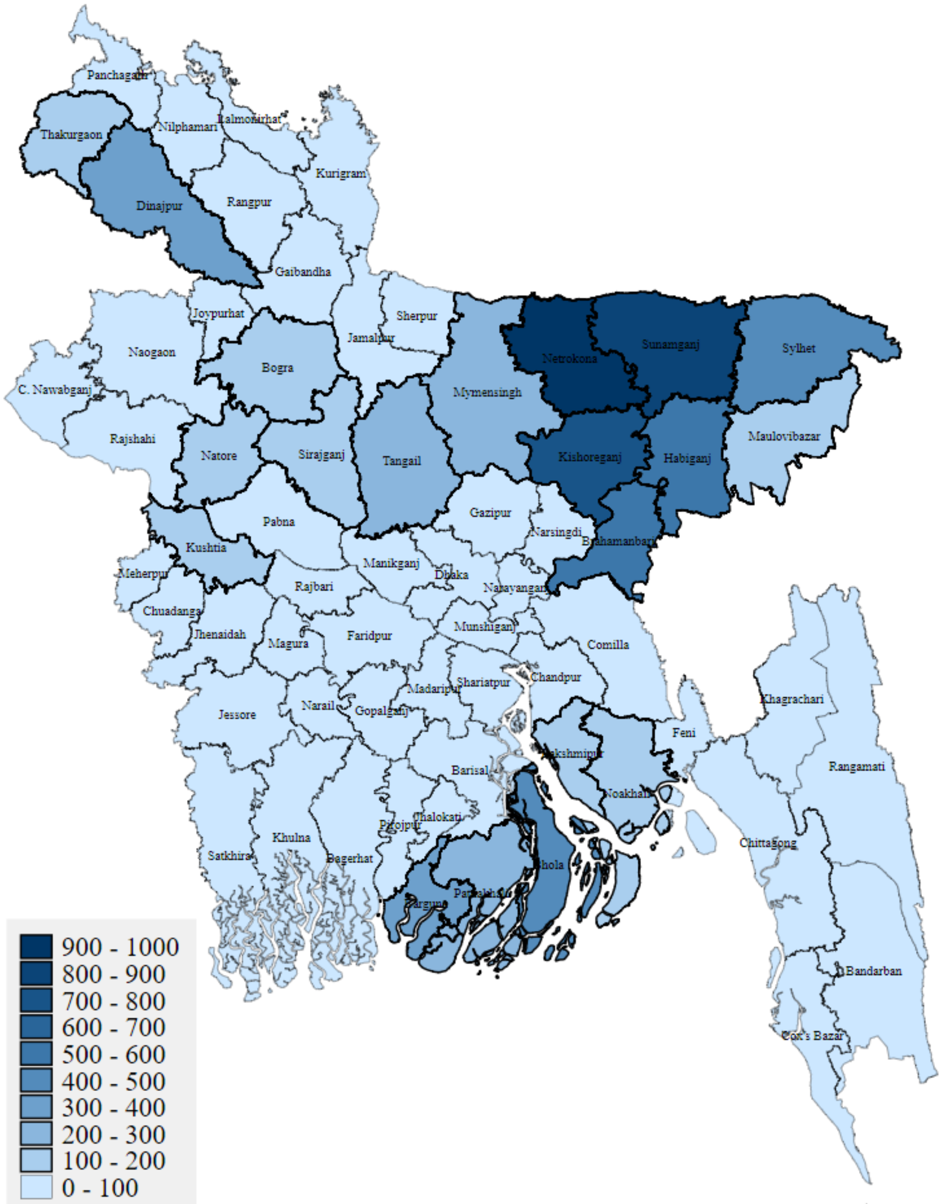
Data

We use three rounds of the Bangladesh Household Income and Expenditure Survey (HIES) - 2010, 2016, and 2022 to examine how agricultural mechanization has influenced rural labor market outcomes. Harmonized data across the three rounds allow us to track changes in employment patterns, including shifts in employment in agriculture and non-agriculture sectors as well as the types of engagement like self-employment, wage labor, and salaried worker. This multi-year structure provides a consistent basis for assessing how mechanization has reshaped rural labor demand and household labor allocation over time.

Empirical Framework

We assess the causal relationship between government-subsidized CH allocations and farming outcomes in Bangladesh in this section. To estimate the impact of CH allocation, we use the canonical difference-in-differences (DiD) method. DiD is an econometric technique widely used in policy analysis to estimate the causal impacts of policy interventions by comparing changes in outcomes over time between treatment and control groups.

Figure 2: Geographical distribution of combine harvesters (2020–2023)



Source: Authors' calculations using DAE's machinery allocation data.

Note: Figures in the legend reflect the number of CHs distributed.

We merge government records on sub-district (upazila) level CH allocations from 2020 to 2022[2] with the HIES rural sample. DAE's official list includes information on 460 sub-districts where CHs were distributed under the mechanization support program. Matching administrative data with the HIES allows the linking of information on farm households from the matched sub-districts. We assume that sub-districts which receive more machines are treatment areas whereas others are control areas. In this regard, we define 75th percentile[3] of CH allocation as our treatment area and below that threshold is our

[2] Though the DAE has records of CH allocation from 2020-23, we restrict the data to 2020-22 for our analysis to coincide with the HIES data collection period.

[3] CH allocation was disproportionate. Below 75th percentile the government allocated 2 harvesters in each sub district while the median value is 6 harvesters. At 75th percentile, government allocated 16 harvesters in each sub districts till 2022.

control area. Since our treatment variable is CH allocation at the 75th percentile, there are 130 "treatment" and 363 "control" upazilas. Table 1 presents the distribution of combine harvester allocation across HIES sampled sub-districts in Bangladesh based on administrative data compiled through 2022.

We use the following equations to estimate the impact of combine harvester allocation on both the extensive and intensive margins. Our analysis on the extensive margin comprises household level participation and intensive margin focuses on individual participation. Equation 1 highlights the extensive margin.

$$Y_{ist} = \alpha_i + \beta_1\, Treatment_i + \beta_2\, Post_t + \beta_3\, (Treatment_i \times Post_t) + \beta_4\, Year_t + \beta_5\, X_{ist} + \beta_6\, Upz_i + \varepsilon_{ist} \quad (1)$$

Here, Y_{ist} denotes the outcome variable of interest for household i, in upazila s, at time t. Outcome variables include household participation in agriculture and non-agriculture economic activities, number of people employed in agriculture and non-agriculture, number of people migrating from households (by gender and migration destination. X_{ist} represents a vector of household characteristics- gender, education and age of the household head, household size and year fixed effects ($Year_t$) to control for time-specific unobserved shocks common across all sub-districts, and sub-district fixed effects (Upz_i) to account for time-invariant characteristics at the sub-district level.

$$Y^g_{ihst} = \alpha_i + \beta_1\, Treatment_i + \beta_2\, Post_t + \beta_3\, (Treatment_i \times Post_t) + \beta_4\, Year_t + \beta_5\, X^g_{ihst} + \beta_6\, Upz_i + \beta_7\, Z_{hst} + \varepsilon_{ist} \quad (2)$$

Equation 2 captures the gender-specific labor force outcome of individual i, in household *h*, in upazila s, at time t. The superscript denotes the gender of the individual, distinguishing between male and female. The labor outcome includes (Y^g_{ihst}) time allocation in agriculture and non-agriculture. X^g_{ihst} is the individual characteristics-including person's age, marital status, years of education. Z_{hst} includes household characteristics such as - household size, work force size, household head's gender, age, and years of schooling.

Findings: Labor Market Impacts and Gender Disparities

Extensive Margin

Following Equation 1 we estimate the causal impact of harvester allocation on rural labor markets on the extensive margin. The results in Table 2 show that mechanization significantly reshapes household labor participation, primarily by shifting the composition of work rather than reducing overall employment. Households in more mechanized areas become more likely to engage in any form of employment, driven mainly by a strong rise in self-employment in agriculture. At the same time, mechanization reduces reliance on wage labor and employee-type jobs, particularly within agriculture, suggesting that machinery reduces demand for hired labor while increasing the productivity and viability of self-run farm activities. In contrast, off-farm employment remains largely unaffected, indicating that the major adjustments in labor allocation occur within the agricultural sector rather than through movement into non-farm work.

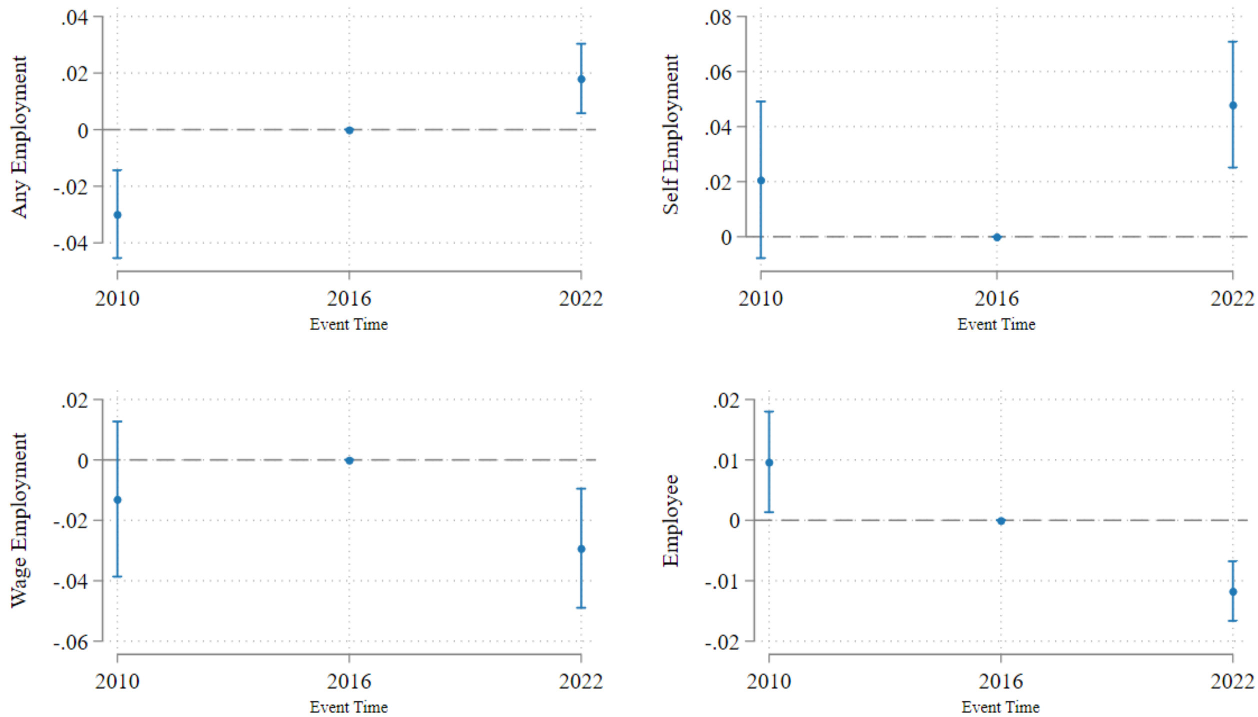
Table 2: Impact of mechanization on labor for participation by households (2016-2022)

Panel A: Any Employment				
	(1)	(2)	(3)	(4)
	Any	Self	Wage	Employee
Post*Treat	0.025**	0.055***	-0.039***	-0.026**
	(0.01)	(0.01)	(0.01)	(0.01)
Control Mean	0.75	0.37	0.48	0.15
Panel B: Agricultural Employment				
	(1)	(2)	(3)	(4)
	Any	Self	Wage	Employee
Post*Treat	0.064***	0.072***	-0.026**	-0.005*
	(0.01)	(0.01)	(0.01)	0.00
Control Mean	0.395	0.251	0.283	0.005
Panel C: Non-Agriculture Employment				
	(1)	(2)	(3)	(4)
	Any	Self	Wage	Employee
Post*Treat	-0.004	-0.015	0.012	-0.011
	(0.015)	(0.012)	(0.013)	(0.012)
Control Mean	0.440	0.137	0.221	0.151

Note: Robust standard errors are in the parenthesis, adjusted for sub-district level clusters and significant at *** p<0.01, ** p<0.05, * p<0.10. Reported control means are without sub-district fixed effects. Outcome variable 'Any Employment' means household's participation in any kind of agricultural work(wage/self-employment/employee) and non-agriculture work (wage/self-employment/employee). All these Panel includes Year and sub-district level fixed effects and are controlled for household characteristics- such as household head's gender, age, years of schooling, work force size, household size. Total number of observations is 37,308. The number of treatment sub-districts is 85, and the number of control sub-districts is 347.

The event study results (See Figure 4) further support the parallel trends assumption and reinforce the main DiD findings. Across all employment categories any employment, self-employment, wage labor, and salaried work, the pre-treatment coefficients remain close to zero and statistically insignificant, indicating no differential trends between treated and control areas before the introduction of combine harvesters. After the intervention, however, the coefficients shift sharply in the expected direction: self-employment rises, while wage and employee positions decline, consistent with mechanization reallocating labor toward own-account agricultural work and reducing demand for hired labor. The post-treatment effects in 2022 closely mirror the magnitudes in the main regression tables, providing strong visual evidence that mechanization drives the observed reorganization of rural labor.

Figure 3: Event study on agricultural employment



Source: Authors' calculation using HIES
Note: Outcome variable 'Any Employment' means household's participation in any kind of agricultural work(wage/self-employment/employee) and non-agriculture work (wage/self-employment/employee).The model includes Year and Sub-district level fixed effects and are controlled for household characteristics- such as household head's gender, age, years of schooling, work force size, household size. The government started to distribute CHs from 2020, so we assume that 2016 as our baseline and 2010 as pre-treatment time and 2022 as post-treatment. The number of treatment sub-districts is 85, and the number of control sub-districts is 347.

The aggregate patterns described above mask critical gender disparities, which we now examine in detail. Tables 3 and 4 present the estimated impacts of the harvester distribution program on male and female employment outcomes across agricultural and non-agricultural activities. The results reveal marked gender asymmetries in the labor-market adjustments to mechanization.

For men, the intervention leads to a modest but statistically significant increase in overall employment, driven primarily by a substantial rise in self-employment (see Table 3). The coefficient for male self-employment in the overall employment category is positive and highly significant, indicating a 4.8 percentage point increase in own-farm related work. This pattern persists within the agricultural sector, where men experience a comparable increase in agricultural self-employment of 5.3 percentage points. At the same time, mechanization appears to reduce male participation in hired farm labor: agricultural wage employment declines significantly by 2.4 percentage points and employee roles fall by 1 percentage point. These results are consistent with the hypothesis that mechanized harvesting reduces the demand for manual field labor while creating opportunities for men to engage in complementary or supervisory tasks associated with mechanized operations. Off-farm employment outcomes for men are largely unaffected, suggesting limited cross-sectoral spillovers.

Table 3: Impact of harvester distribution on Male Employment

Panel A: Overall Employment				
	(1)	(2)	(3)	(4)
	Any	Self	Wage	Employee
Post*Treat	0.017*	0.048***	-0.012	-0.020*
	(0.009)	(0.014)	(0.014)	(0.012)
Control Mean	0.736	0.361	0.384	0.141
Panel B: Agricultural Employment				
	(1)	(2)	(3)	(4)
	Any	Self	Wage	Employee
Post*Treat	0.022	0.053***	-0.024**	-0.010***
	(0.014)	(0.014)	(0.012)	(0.003)
Control Mean	0.382	0.251	0.223	0.004
Panel C: Non-Agriculture Employment				
	(1)	(2)	(3)	(4)
	Any	Self	Wage	Employee
Post*Treat	-0.004	-0.005	0.005	-0.013
	(0.014)	(0.012)	(0.012)	(0.011)
Control Mean	0.417	0.132	0.181	0.137

Note: Robust standard errors are in the parenthesis, adjusted for sub-district level clusters and significant at *** p<0.01, ** p<0.05, * p<0.10. Reported control means are without sub-district fixed effects. Outcome variable 'Any Employment' means household's participation in any kind of agricultural work(wage/self-employment/employee) and non-agriculture work (wage/self-employment/employee). All of these Panel includes Year and sub-district level fixed effects and are controlled for household characteristics- such as household head's gender, age, years of schooling, work force size, household size. Total number of observations is 37,308. The number of treatment sub-districts is 85, and the number of control sub-districts is 347.

In contrast, women exhibit significant reductions in labor market participation, particularly in activities most directly replaced by mechanized harvesting. Historically, women are engaged in post-harvesting related activities such as threshing, sorting, and packaging of grains. Combine harvesting can do all these activities - all together and thus reduces the demand for female labor time in those post-harvesting activities. Overall, the probability of female employment falls by 1.8 percentage points, with the decline concentrated in self-employment by 3.4 percentage points. The negative effects are even more pronounced in agriculture: agricultural self-employment decreases by 2.6 percentage points, and female employment as hired workers also declines 0.2 percent, despite the exceptionally low baseline for employee roles. These findings imply that mechanization disproportionately displaces women from agricultural tasks, many of which traditionally involve manual harvesting and post-harvest processing. Unlike men, women do not compensate for these losses through increased participation in off-farm work.

Off-farm self-employment declines slightly by 0.8 percentage points, and other non-farm work categories show no significant adjustments, indicating limited capacity for women to transition into alternative income-generating activities.

Taken together, the results demonstrate that the harvester distribution program benefits male workers more than female workers, both in terms of increased labor opportunities and the ability to shift into self-employment roles linked to mechanized production. For women, mechanization leads to a contraction of labor participation, with no observable compensatory movement toward non-agricultural employment. These patterns underscore how mechanization, in the absence of complementary gender-sensitive interventions, can exacerbate existing gender disparities in rural labor markets.

Table 4 : Impact of harvester distribution on Female Employment

Panel A: Overall Employment				
	(1)	(2)	(3)	(4)
	Any	Self	Wage	Employee
Post*Treat	-0.018*	-0.034***	-0.000	0.001
	(0.011)	(0.011)	(0.006)	(0.006)
Control Mean	0.086	0.261	0.045	0.023
Panel B: Agricultural Employment				
	(1)	(2)	(3)	(4)
	Any	Self	Wage	Employee
Post*Treat	-0.010	-0.026**	0.000	-0.002**
	(0.008)	(0.010)	(0.004)	(0.001)
Control Mean	0.020	0.251	0.022	0.000
Panel C: Non-Agriculture Employment				
	(1)	(2)	(3)	(4)
	Any	Self	Wage	Employee
Post*Treat	-0.007	-0.008*	-0.001	0.003
	(0.008)	(0.004)	(0.005)	(0.006)
Control Mean	0.047	0.012	0.024	0.023

Note: Robust standard errors are in the parenthesis, adjusted for sub-district level clusters and significant at *** p<0.01, ** p<0.05, * p<0.10. Reported control means are without sub-district fixed effects. Outcome variable 'Any Employment' means household's participation in any kind of agricultural work(wage/self-employment/employee) and non-agriculture work (wage/self-employment/employee). All these Panel includes Year and sub-district level fixed effects and are controlled for household characteristics- such as household head's gender, age, years of schooling, work force size, household size. Total number of observations is 37,308. The number of treatment sub-districts is 85, and the number of control sub-districts is 347.

Table 5 shows that the distribution of harvesters has a significant effect on household migration decisions. The positive and significant coefficient for any migration (4.5 percentage points) indicates that households in treated sub-districts are more likely to send at least one migrant compared to the control mean of 12%. This increase is driven almost entirely by foreign migration, which rises by 6.1 percentage points, an effect that is both large and statistically strong relative to the baseline rate of 8.5%. In contrast, domestic migration decreases slightly by 1.3 percentage points. Together, these results suggest that mechanization, by reducing the need for agricultural wage labor and freeing up household members from seasonal farm work, enables or incentivizes households to pursue more lucrative overseas opportunities rather than internal migration.

Table 5: Impact of harvester distribution on migration (2016-2022)

	(1)	(2)	(3)
	Any	Domestic	Foreign
Post*Treat	0.045***	-0.013**	0.061***
	(0.01)	(0.01)	(0.01)
Control Mean	0.120	0.038	0.085

Note: Robust standard errors are in the parenthesis, adjusted for sub-district level clusters and significant at *** p<0.01, ** p<0.05, * p<0.10. Reported control means are without sub-district fixed effects Outcome variable takes a value 1 of household report any migration and otherwise 0. Total number of observations is 37,308. The number of treatment sub-districts is 85, and the number of control sub-districts is 347.

Intensive Margin

We measure the causal impact of harvester allocation on agricultural wage labor and self-employed people following Equation 2. CH machines can significantly reduce the labor time for both family and hired labor. If the family labor time is saved from crop production, households can allocate their time in other agricultural tasks like livestock rearing and fisheries production, which can also be considered as a measure of agricultural employment.

Tables 6 and 7 together show that the distribution of combine harvesters produced opposite shifts in agricultural labor allocation for wage workers and the self-employed. Table 6 on agricultural wage labor indicates a consistent decline in wage-based participation, particularly among men: treated sub-districts experience significant reductions in months and days worked in wage employment, although wage rates slightly increase. This pattern suggests that mechanization by reducing peak-season labor demand compresses the volume of wage work available. In contrast, Table 7 shows that self-employment in agriculture increases after harvester distribution, with treated households working more days and substantially more hours per month and year. These gains are strongest for pooled and female workers, indicating that mechanization may free up household labor, allowing farmers especially women to allocate more time to their own farm activities rather than relying on wage labor. Overall, the results point to a reallocation of labor away from agricultural wage work and toward self-employment, driven by mechanization-induced changes in labor requirements and productivity.

Table 5 : Impact of harvester distribution on agriculture wage labor (2016-2022)

Panel A: Pooled (Male and Female)					
	(1)	(2)	(3)	(4)	(5)
	Months	Days	Hours (Monthly)	Hours(yearly)	Wage
Post*Treat	-0.838***	-0.758*	4.292	-93.439	22.471*
	(0.216)	(0.393)	(4.185)	(57.394)	(11.963)
Control Mean	10.041	21.413	174.730	1776.456	259.056
Panel: B: Male					
	(1)	(2)	(3)	(4)	(5)
Post*Treat	-0.815***	-0.596	5.248	-84.186	18.903
	(0.222)	(0.404)	(4.329)	(59.269)	(11.914)
Control Mean	10.105	21.589	176.593	1805.815	265.609
Panel C: Female					
	(1)	(2)	(3)	(4)	(5)
Post*Treat	1.375	-3.741	-19.353	173.398	3.990
	(1.691)	(2.796)	(25.011)	(382.759)	(41.409)
Control Mean	9.348	19.498	154.457	1457.008	187.753

Note: Robust standard errors are in the parenthesis, adjusted for sub-district level clusters and significant at *** p<0.01, ** p<0.05, * p<0.10. Reported control means are without sub-district level fixed effects. Outcome variables are time allocation of agricultural wage workers. “Month” is measured as number of months worked as a self-employed in agriculture, “Day" is measured as number of days worked in a month, “Hour(monthly)” is measured as = number of hours worked in a day x number of days worked in a month. “Hour(yearly)” is measured as = number of hours worked in a day x number of days worked in a month x number of months worked in a year. “Wage” is measured as average daily wage. Individual controls include- sex, age, marital status, education, and household control includes - household size, work force size, household head's education, gender, farm or not. Panel A has a sample size of 9183 observations; Panel B has 8590 and Panel C has 573 observations. The number of treatment sub-districts is 85, and the number of control sub-districts is 347.

In contrast, Table 7 shows that self-employment time allocation in agriculture increases in the treated areas. These gains are strongest for the pooled model and female regressions, indicating that mechanization may free up household labor, allowing women to allocate more time to their own farm activities (specially in livestock and fisheries) rather than relying on wage labor. Although we observe from Table 4 a reduction in overall self-employment participation for women in agriculture, together, these findings point to a shift in how households engage in self-employment. This indicates that while fewer women remain self-employed overall, those who do are allocating substantially more time to these activities, likely due to labor saved through mechanization.

Overall, the results point to a reallocation of labor away from agricultural wage work and toward self-employment, driven by mechanization-induced changes in labor requirements and productivity.

Table 6 : Impact of harvester distribution on self-employment in agriculture (2016-2022)

Panel A: Pooled Model (male and female)

	(1)	(2)	(3)	(4)
	Months	Days	Hours (Monthly)	Hours(yearly)
Post*Treat	0.291*	0.867**	11.368***	122.515**
	(0.156)	(0.357)	(3.967)	(49.295)
Control Mean	9.762	21.344	150.680	1517.089

Panel B: Male

	(1)	(2)	(3)	(4)
Post*Treat	-0.008	0.608	10.424**	79.889
	(0.164)	(0.377)	(4.181)	(51.955)
Control Mean	9.76	21.37	151.39	1524.67

Panel C: Female

	(1)	(2)	(3)	(4)
Post*Treat	4.187*	13.048***	52.206	859.336
	(1.993)	(3.200)	(38.512)	(451.173)
Control Mean	9.75	20.82	132.61	1323.64

Note: Robust standard errors are in the parenthesis, adjusted for sub-district level clusters and significant at *** p<0.01, ** p<0.05, * p<0.10. Reported control means are without sub-district fixed effects Outcome variables are time allocation of self-employed people in agriculture. “Month” is measured as number of months worked as a self-employed in agriculture, “Day'' is measured as number of days worked in a month, “Hour(monthly)” is measured as = number of hours worked in a day x number of days worked in a month. “Hour(yearly)” is measured as = number of hours worked in a day x number of days worked in a month x number of months worked in a year. Individual controls include- sex, age, marital status, education, and household control includes - household size, work force size, household head's education, gender, farm or not. Panel A has a sample size of 10121 observations; Panel B has 9225 and Panel C has 826 observations. The number of treatment sub-districts is 85, and the number of control sub-districts is 347.

Conclusion

Overall, the evidence shows that combine harvester distribution has reshaped rural labor markets not by reducing employment, but by reallocating labor within agriculture. Mechanization increases households’ likelihood of engaging in any employment and substantially raises agricultural self-employment, particularly among men. At the same time, reliance on agricultural wage labor declines, indicating that mechanization compresses seasonal labor demand while creating opportunities for own-account agricultural work. These effects are concentrated in agriculture, with virtually no spillover into non-agricultural employment.

Importantly, the labor market adjustments are strongly gender differentiated. Men benefit from expanded self-employment opportunities linked to mechanized operations, whereas women experience declining participation in self-employment activities. The results imply that mechanization substitutes for tasks that women traditionally perform, without generating alternative work pathways for them. Consequently, the program unintentionally widens gender gaps in agricultural labor engagement.

On the intensive margin, the evidence reinforces these conclusions: the volume of wage labor falls in treated areas, while remaining self-employed persons particularly women- increase the amount of time devoted to their own agricultural activities. This suggests that family labor saved through mechanization is reallocated toward complementary farm enterprises (e.g., livestock and fisheries), rather than toward off-farm work. In addition, increased foreign migration among treated households indicates that mechanization relaxes seasonal labor constraints and enables households to pursue more profitable overseas opportunities.

Taken together, the findings demonstrate that mechanization alters the structure rather than the level of rural labor use, shifts labor toward self-employment, and yields starkly uneven consequences across genders. The Phase III program, while successful in boosting productivity and reducing costs (Bakhtiar et al. 2025), has unintentionally widened gender gaps in agricultural labor engagement. Without complementary interventions that expand women's access to mechanized opportunities, provide skills training for alternative employment, or create targeted support for women-led agricultural enterprises, mechanization risks reinforcing existing gender disparities. Future phases of Bangladesh's mechanization program should explicitly incorporate gender-sensitive design—including quotas for women MSP operators, training programs for women in machine operation and maintenance, and support for women's participation in livestock and fisheries enterprises that can absorb displaced labor. Ensuring that the gains from agricultural modernization are broadly shared requires deliberate policy attention to gender equity.

ABOUT THE AUTHORS

Moogdho M. Mahzab (M.Mahzab@cgiar.org) is a Research Fellow in the Poverty, Gender, and Inclusion (PGI) Unit at the International Food Policy Research Institute (IFPRI).

M. Mehrab Bakhtiar (M.Bakhtiar@cgiar.org) is a Research Fellow in the PGI Unit at IFPRI.

Md. Aminul Karim (M.A.Karim@cgiar.org) is Research Analysts in the PGI Unit at IFPRI.

Agnes Quisumbing (A.Quisumbing@cgiar.org) is a Senior Research Fellow in the PGI Unit at IFPRI.

Shalini Roy (S.Roy@cgiar.org) is a Senior Research Fellow in the PGI Unit at IFPRI.

ACKNOWLEDGMENTS

The CGIAR Gender Equality and Inclusion Accelerator and the Gates Foundation provided funding for this work. This publication has not been independently peer reviewed. Any opinions expressed here belong to the authors and are not necessarily representative of or endorsed by IFPRI or CGIAR.

REFERENCES

Afridi, Farzana, Monisankar Bishnu, and Kanika Mahajan. 2023. “Gender and Mechanization: Evidence from Indian Agriculture.” *American Journal of Agricultural Economics* 105 (1): 52–75. https://doi.org/10.1111/ajae.12315.

Ahammad, Sharif, Mohammad Mizanul Haque Kazal, Monira Sultana, and Md. Hayder Khan Sujan. 2025. “Technical Efficiency of Combine Harvester User Boro Rice Farmers in Haor Ecosystem of Bangladesh.” *Discover Agriculture* 3 (1): 66. https://doi.org/10.1007/s44279-025-00213-8.

Bakhtiar, M Mehrab, Moogdho M Mahzab, Aminul Karim, et al. 2025. “Agricultural Mechanization Policy in Bangladesh : An Assessment of the Phase III Support Program and Recommendations for Reform.” International Food Policy Research Institute (IFPRI), July. https://cgspace.cgiar.org/server/api/core/bitstreams/4ce57cee-5d92-4b92-911b-cd1728d4b4e4/content.

Belton, Ben, Peixun Fang, and Thomas Reardon. 2024. “Combine Harvester Outsourcing Services and Seasonal Rural Non-Farm Employment in Myanmar.” *Applied Economic Perspectives and Policy* 1–28. https://doi.org/10.1002/aepp.13480.

Caunedo, Julieta, and Namrata Kala. 2022. “Mechanizing Agriculture.” Working Paper. http://www.nber.org/papers/w29061.

Karim, Md Aminul, Raisa Shamma, M Mehrab Bakhtiar, Ben Belton, Avinash Kishore, and Akhter U. Ahmed. 2024. “Mechanizing Agriculture in Bangladesh: Trends, Challenges, and Policy Priorities.” Paper presented at Mechanization of Small-Scale Farms in Asia: Current Status, Impacts, and Future Prospects. April.

Ma, Wanglin, Xiaoshi Zhou, David Boansi, Godwin Seyram Agbemavor Horlu, and Victor Owusu. 2024. “Adoption and Intensity of Agricultural Mechanization and Their Impact on Non-Farm Employment of Rural Women.” *World Development* 173 (January): 106434. https://doi.org/10.1016/j.worlddev.2023.106434.

Meng, Meng, Leng Yu, and Xiaohua Yu. 2024. “Machinery Structure, Machinery Subsidies, and Agricultural Productivity: Evidence from China.” *Agricultural Economics*, February 6, agec.12820. https://doi.org/10.1111/agec.12820.

Rahman, Md Mostafizar, Md Rostom Ali, Md Moinul Hosain Oliver, et al. 2021. “Farm Mechanization in Bangladesh: A Review of the Status, Roles, Policy, and Potentials.” *Journal of Agriculture and Food Research* 6 (December): 100225. https://doi.org/10.1016/j.jafr.2021.100225.

Sujan, Md. Hayder Khan, Mou Rani Sarker, Md Abdur Rouf Sarkar, et al. 2025. “Harnessing Rice Combine Harvester Adoption for Sustainable Agriculture in the *Haor* (*Wetland*) Ecosystem of Bangladesh.” *Australian Journal of Agricultural and Resource Economics* 69 (4): 836–54. https://doi.org/10.1111/1467-8489.70055.

Vortia, Pooja, Mahmuda Nasrin, Shahana Khatun Bipasha, and Md. Monirul Islam. 2021. “Extent of Farm Mechanization and Technical Efficiency of Rice Production in Some Selected Areas of Bangladesh.” *GeoJournal* 86 (2): 729–42. https://doi.org/10.1007/s10708-019-10095-1.

Zheng, Hongyun, Wanglin Ma, Yanzhi Guo, and Xiaoshi Zhou. 2022. “Interactive Relationship between Non-Farm Employment and Mechanization Service Expenditure in Rural China.” *China Agricultural Economic Review* 14 (1): 84–105. https://doi.org/10.1108/CAER-10-2020-0251.

Zou, Baoling, and Ashok K. Mishra. 2024. “Modernizing Smallholder Agriculture and Achieving Food Security: An Exploration in Machinery Services and Labor Reallocation in China.” *Applied Economic Perspectives and Policy*, March 27, aepp.13433. https://doi.org/10.1002/aepp.13433.