Chapter 02: In-Kind Incentives and Wage Outcomes: An Econometric Analysis

Abstract

The factors that determine farm workers' wages in agriculture-intensive rural economies remain a subject of debate among economists. Wage dynamics among marginalized populations are central to understanding welfare distribution, particularly in agrarian developing countries. While past studies have examined economic and environmental drivers of agricultural wages, they have largely overlooked non-monetary incentives—especially employer-provided meals—that remain widespread in informal labor markets. This study addresses that gap using district-level panel data and a two-stage instrumental variable (IV) estimation strategy. In the first stage, we estimate rice yield based on climatic variables such as growing degree days, extreme heat, and precipitation. In the second stage, we examine how predicted yield and meal provision affect real agricultural wages. Preliminary results suggest that higher yields are associated with lower wages, challenging standard economic assumptions. We also document persistent wage disparities across seasons, districts, and genders, and find that meal provision significantly influences wage outcomes. These findings help explain why many agricultural workers leave the sector, even as crop productivity increases.

Contents

1. Introduction

Agricultural labor markets in many developing countries are informal—lacking written contracts, and seasonal, with labor needs peaking during planting and harvest seasons and dropping sharply in between Ryan (2023); International Labour Organization, ILOSTAT (2024); Osadolor (2024). Daily wages are mostly negotiated verbally and paid in cash, but during peak farming periods, employers often supplement payment with cooked meals (Mizik, Nagy, Molnár, et al., 2025). These practices are common in smallholder-dominated regions facing food insecurity and low cash availability. Although recent studies have examined cash wage patterns and minimum wage compliance Mansoor and O'Neill (2021); Espinosa, Bejarano, Arias, and González (2025), few have explicitly quantified the role of in-kind incentives such as meals. Understanding this aspect is important for understanding the wage determining factors, specially in agriculture intensive economy.

Despite being common in rural agricultural settings across South and Southeast Asia, the use of meals as part of worker compensation has received little attention in quantitative wage analysis. While household surveys and qualitative studies often mention meal provision, it is rarely included as a separate regressor in econometric models of wage determination. Instead, such models typically focus on factors like education Tran, Pham, and Nguyen (2023); Van Vu (2020), gender and land access S. Rahman (2000), or the division between on-farm and off-farm income sources.

This study investigates how non-monetary incentives—specifically, meal provision, affect wage outcomes in informal agricultural labor markets. Focusing on rural Bangladesh, where agriculture is labor-intensive and contracts are typically verbal, it examines how meals, commonly provided during the workday, substitute for cash wages and shape total compensation. Using detailed district-level panel data, the study tests whether meal provision systematically reduces cash wages and whether this effect varies by season, location, and gender. A two-stage fixed effects instrumental variable (IV) strategy is employed: crop yields are first predicted using climatic instruments such as growing degree days, extreme degree days, and precipitation; then real wages are regressed on these predicted yields, meal provision, and other controls. By explicitly modeling meals as a regressor—unlike most prior wage studies—this approach estimates how much cash wages are reduced when meals are provided instead. In doing so, the study offers the first econometric evidence, at the subnational level, on how discrete meal incentives shape real wages in rural, labor-intensive agricultural settings.

The remainder of the thesis is organized as follows. Section 2 presents a structured review of theoretical and empirical literature on wage formation, focusing on informal labor markets and non-monetary compensation.

Section 3 outlines the econometric methodology, including the two-stage IV design and fixed effects structure used to identify causal relationships.

Section 4 describes the data sources and construction of the panel dataset, including district-level wage, climate, and crop yield variables.

Section 5 presents the empirical findings, organized by the three core hypotheses related to yield, meal provision, and gender wage differences. Section 6 concludes by outlining directions for future extensions involving other crops, input costs, and seasonal dynamics.

2. Literature Review

In labor-intensive, low-mechanization rural economies undergoing structural transition, non-monetary compensation remains a common feature of agricultural wage arrangements. One prevalent form is the provision of meals by employers. This practice is especially relevant in settings where food insecurity persists, wage negotiations are informal and verbal, and labor markets remain unstructured and seasonal. While such arrangements are well acknowledged in theoretical literature Gupta (1989); Datta, Nugent, and Tishler (2004); Powell and Murphy (2015), their role in shaping wage-setting practices has typically been discussed in conceptual terms rather than examined through formal empirical modeling.

Theoretical studies often explain why employers in informal rural labor markets provide a mix of cash and meals instead of paying only in money. Efficiency wage models suggest that when workers' productivity depends on nutrition, providing food can be a cost-effective way to sustain labor effort—especially in contexts of food scarcity or household burdens Gupta (1989). Other frameworks, such as risk-sharing models, argue that meals help stabilize workers' consumption in the absence of formal credit or insurance Datta et al. (2004). Some extensions even incorporate the caloric value of meals to explore their broader labor market effects Powell and Murphy (2015). Yet despite these insights, none of these studies use meals as a discrete regressor or estimate their marginal impact on agricultural wages using econometric methods.

Empirical studies on agricultural wage determination have applied a range of econometric approaches, including OLS Boyce and Ravallion (1991); Ravallion (1990), first-difference models Lasco, Myers, and Bernsten (2008), fixed effects and panel regressions Mahajan (2015); Nguyen (2006); Kumar et al. (2020), and instrumental variable techniques such as 2SLS and IV panel models Emran and Shilpi (2018); Merfeld (2019). These studies typically focus on real daily or monthly wages as the dependent variable and include determinants such as rice prices (Rashid, 2002; Ravallion, 1990), agricultural productivity (R. Palmer-Jones & Parikh, 1998; Emran & Shilpi, 2018), public works programs and non-farm employment (Mahajan, 2015; Venkatesh, 2013), mechanization (Kumar et al., 2020), literacy (Kundu & Sangita, 2019), gender wage disparities (Srivastava, Sengupta, et al., 2016), and seasonal shocks like floods (Banerjee, 2007). Structural factors such as cropping intensity, tenancy, and rural population pressure are also considered (Ahmed, 1981; Boyce, 1989).

Country-specific studies from Bangladesh, India, the Philippines, and Vietnam consistently highlight recurring wage determinants—such as rice prices, agricultural productivity, non-farm employment, mechanization, and demographic pressure (Boyce & Ravallion, 1991; R. W. Palmer-Jones, 1993; Lasco et al., 2008; Nguyen, 2006; A. Hossain, 1990; Kumar et al., 2020). These relationships are typically modeled using time-series and panel regressions, or structural models to address causality and policy effects R. Palmer-Jones and Parikh (1998); M. I. Rahman (2007); Hanchate and Ramaswamy (1997). However, despite substantial empirical attention to wage dynamics, the role of discrete non-monetary incentives—particularly meals—has not been isolated in formal econometric analysis.

Building on the established literature, we now focus specifically on studies using fixed effects (FE) or instrumental variable (IV) approaches to estimate the impact of in-kind benefits on agricultural wages. While theoretical models suggest that employer-provided goods—such as meals, housing, or transport—should induce compensating wage differentials (Gupta, 1989; Datta et al., 2004), no empirical study in the reviewed literature directly estimates their separate effects using modern FE or IV frameworks. The closest attempt is by Ito and Kurosaki (2009), who apply a Tobit model to aggregate in-kind and cash wages, showing that in-kind payments (mainly food) rise during adverse weather or food price shocks—suggesting a food security rationale. However, they do not distinguish between benefit types, estimate wage pass-through, or control for fixed effects (Pushpangadan, 2010). Studies like Das and Usami (2017) and Powell and Murphy (2015) use FE or IV approaches, but focus on gender or sectoral wage differences without modeling in-kind transfers. Thus, despite consistent theoretical interest in compensating differentials, the empirical literature has yet to identify the wage effects of discrete meal provision through credible causal designs.

Historical panel and time-series studies in agrarian economies—particularly in South Asia—have examined how agricultural wages respond to structural, demographic, and macroeconomic factors. Early research explored the roles of land distribution, tenancy arrangements, landlessness, and population pressure in shaping rural labor markets (Ahmed, 1981; Khan, 1984). Others linked agricultural output and labor productivity to real wage changes, incorporating variables such as rural population density, rice prices, and non-agricultural wage trends into dynamic wage models (A. Hossain, 1990; Boyce, 1989; Boyce & Ravallion, 1991). Price transmission effects, especially via food price fluctuations, have also been studied as key channels for rural welfare shifts (Ravallion, 1990). Later work revisited and challenged some of these earlier claims—arguing, for instance, that agricultural growth exerted stronger positive effects on wages than previously estimated (R. W. Palmer-Jones, 1993). More recent contributions employed time-series approaches such as bivariate correlation, cointegration, and ARDL models to test long- and short-run relationships between productivity and rural wages (Rashid, 2002; A. A. Hossain, 2022). However, none of these studies incorporate in-kind benefits in their empirical specifications—a gap this study directly addresses.

This study uses recorded data on meal provision and includes it directly in sub national panel wage regressions. Instead of treating meals as a background factor, we use them to explain daily agriculture labor wages in a agriculture intensive economy. This enable us to examine whether meals substitute for cash wages, enhance compensation beyond their cash equivalent, or both. By bringing this unmeasured but widely practiced form of in-kind compensation into empirical focus, our study extends the wage determination literature and offers new insight into how agricultural wages are structured in informal, labor-intensive rural economies.

3. Methodology

This study applies a two-stage instrumental variable (IV) approach to examine how agricultural productivity affects real agricultural wages, with a focus on the role of employer-provided meals.

This approach is used to address the possibility that rice yield and wages may be related through more than a simple cause-and-effect relationship. For example, unobserved factors such as district-specific farming conditions or labor availability could influence both yield and wages at the same time. Additionally, higher wages might enable better inputs or attract higher-quality labor, which could in turn raise productivity. To address these challenges, rice yield is treated as an endogenous variable, and climate-based instruments are used to isolate variation in yield that is independent of labor market factors.

In the first stage, yield is modeled using climate variables that influence crop growth but are unlikely to be connected to local wage-setting. Specifically, we use Growing Degree Days (GDD), Extreme Degree Days (EDD), and precipitation, all measured at the district and growing-season level. These variables are widely used in agricultural econometrics because they capture biologically relevant weather patterns while remaining exogenous to local wage structures.

In the second stage, the predicted yield values from the first stage are used to estimate their effect on real agricultural wages. The outcome variable is the daily wage, adjusted for inflation, and disaggregated by gender and the number of meals provided as part of compensation.

To account for unobserved heterogeneity, the model includes fixed effects for district, year, and growing season. This helps ensure that the estimates are not confounded by differences across locations or time periods that do not vary within those units.

3.1. First Stage

To analyze the impact of climatic variables on agricultural yields, we employ a first-difference approach, a widely used econometric technique for controlling for time-invariant unobservable characteristics and capturing short-term fluctuations due to external shocks. This method ensures that fixed factors, do not confound the estimated relationships between climate variables and yield outcomes.

The first-difference transformation is applied to the log-transformed yield to account for proportional changes rather than absolute differences. The first difference of log yield is computed as:

$$\Delta \log(\text{Yield}_{it}) = \log(\text{Yield}_{it}) - \log(\text{Yield}_{it-1}) \tag{1}$$

where i indexes districts and t indexes years.

Using OLS:

$$\begin{aligned}\boldsymbol{\Delta}\,\mathbf{log}(\text{Yield}_{\boldsymbol{i,t,s}}) = {} & \boldsymbol{\beta_1}\boldsymbol{\Delta}\text{GDD}_{\boldsymbol{i,t,s}} + \boldsymbol{\beta_2}\boldsymbol{\Delta}\text{EDD}_{\boldsymbol{i,t,s}} + \boldsymbol{\beta_3}\boldsymbol{\Delta}\text{Precip}_{\boldsymbol{i,t,s}} \\ & + \boldsymbol{\beta_4}(\boldsymbol{\Delta}\text{GDD}_{\boldsymbol{i,t,s}} \times \boldsymbol{\Delta}\text{Precip}_{\boldsymbol{i,t,s}}) + \boldsymbol{\gamma_i} + \boldsymbol{\delta_t} + \boldsymbol{\theta_s} \\ & + \boldsymbol{\lambda_{i,s}} + \boldsymbol{\kappa_{t,s}} + \boldsymbol{\epsilon_{i,t,s}}\end{aligned} \tag{2}$$

In this specification, $\Delta\text{GDD}_{i,t,s}$, $\Delta\text{EDD}_{i,t,s}$, and $\Delta\text{Precip}_{i,t,s}$ represent first-differenced measures of Growing Degree Days, Extreme Degree Days, and precipitation, respectively. The terms γ_i, δ_t, and θ_s denote fixed effects for district, year, and growing season. In addition, the model includes district-by-season fixed effects ($\lambda_{i,s}$) and year-by-season fixed effects ($\kappa_{t,s}$) to account for unobserved seasonal patterns that may vary across space and time. The error term $\epsilon_{i,t,s}$ is clustered at the district level to allow for serial correlation within districts.

3.1.1 Reconstructing Yield Predictions from Differenced Estimates

Since the model estimates log-differenced yield, we reconstruct predicted yield levels using a cumulative summation technique, following the approach of Dell, Jones, and Olken (2012), where cumulative changes are summed to approximate level values.

First, the predicted change in log yield is obtained as:

$$\Delta\,\widehat{\log(\text{Yield})}_{it} = X_{it}\widehat{\beta} \tag{3}$$

where X_{it} represents the matrix of explanatory variables. The reconstructed log yield is then computed by cumulatively summing the predicted differences:

$$\log(\widehat{\text{Yield}}_{it}) = \log(\text{Yield}_{i1}) + \sum_{s=2}^{t} \Delta\,\widehat{\log(\text{Yield})}_{is} \tag{4}$$

Exponentiating both sides gives the predicted yield in levels:

$$\widehat{\text{Yield}}_{it} = \exp(\log(\widehat{\text{Yield}}_{it})) \tag{5}$$

This approach ensures that the predicted yield retains a consistent proportional relationship to the baseline year, while allowing for year-to-year variation driven by climatic factors.

3.2. Second Stage

The second stage of the instrumental variable (IV) analysis estimates how changes in agricultural productivity, represented by predicted rice yield, affect real agricultural wages.

The model also tests whether this effect varies based on the inclusion of meals as part of worker compensation. The regression includes fixed effects for district, year, and growing season to control for location-specific, temporal, and seasonal factors. A district-by-year interaction term is added to capture additional variation in local wage dynamics over time.

$$\begin{aligned} \text{RealWage}_{i,t,s} &= \beta_0 + \beta_1 \hat{\text{Yield}}_{i,t,s} + \beta_2 \text{Gender}_{i,t,s} + \beta_3 \text{WageType}_{i,t,s} \\ &\quad + \gamma_i + \delta_t + \theta_s + (\gamma_i \times \delta_t) + \varepsilon_{i,t,s} \end{aligned} \tag{6}$$

In this specification, $RealWage_{i,t,s}$ denotes the inflation-adjusted daily wage in district i, year t, and growing season s. The main explanatory variable, $\widehat{Yield}_{i,t,s}$, represents the predicted rice yield from the first stage. $Gender_{i,t,s}$ is a binary indicator for male or female workers, and $WageType_{i,t,s}$ indicates whether the wage includes meals or is paid entirely in cash. The terms γ_i, δ_t, and θ_s represent district, year, and growing season fixed effects, respectively. The model also includes a district-by-year interaction term, $(\gamma_i \times \delta_t)$, to capture time-varying district-level factors. The error term $\varepsilon_{i,t,s}$ is clustered at the district level.

3.3. Hypotheses

The first stage of the model is used to generate predicted values of rice yield using climatic variables. While the coefficients on Growing Degree Days (GDD), Extreme Degree Days (EDD), and precipitation are interpreted, the primary purpose of this stage is to ensure that these instruments are relevant and strongly predictive of yield. The main hypotheses tested in this study pertain to the second-stage wage outcomes:

- **H1:** Higher agricultural yield increases real agricultural wages.
- **H2:** Receiving meals as part of compensation lowers the cash wage received by workers.
- **H3:** Male workers receive higher wages than female workers for comparable work.

4. Data

This study relies on a district-level panel dataset covering the period from 2014 to 2023 in Bangladesh. The dataset includes monthly and annual records on agricultural wages, employer-provided meals, rice yields, land use, and climatic variables such as temperature and rainfall. These data are used to examine how meals provided by employers influence agricultural wages over time, across districts.

4.1. Wage and Meal Provision Data

Monthly wage data were collected at the district level and include separate observations by gender and type of compensation. In addition to the wage amount, the dataset records whether meals were provided with payment and, if so, whether workers received one, two, or three meals per day. Another variable indicates whether the wage was paid with or without meals, allowing both binary and detailed meal-based analysis. Nominal wages were adjusted using the monthly Consumer Price Index (CPI) to calculate real wages, ensuring that wage comparisons over time account for inflation. All wage-related data, including information on meal provision and CPI, were collected from the *Yearbook of Agricultural Statistics (2013–2023)*, published by the Bangladesh Bureau of Statistics Bangladesh Bureau of Statistics (2014–2024).

4.2. Agricultural Production Data

Annual district-level rice production data—covering yield per acre and hectare, total output in metric tons, and cultivated area—were compiled for the three dominant rice variants: Aus, Aman, and Boro. These variables capture spatial and temporal variation in agricultural productivity, which is central to identifying how wage levels respond to changes in output. All production data were collected from the *Yearbook of Agricultural Statistics* (2013–2023), published by the Bangladesh Bureau of Statistics Bangladesh Bureau of Statistics (2014–2024).

4.3. Land Use Data

District-level annual land use data provide information on agricultural intensity, including cultivated land, current net cropped area, and fallow categories. These variables help account for structural differences in land use across districts. By including them, the analysis controls for the possibility that wage variation is driven by differences in cropping density or land availability rather than the provision of meals. This helps ensure that any observed association between meals and wages reflects actual differences in compensation practices, rather than variation in land use conditions. All land use data were collected from the *Yearbook of Agricultural Statistics* (2013–2023), published by the Bangladesh Bureau of Statistics Bangladesh Bureau of Statistics (2014–2024).

4.4. Climate and Weather Data

Monthly climate data on temperature and precipitation were obtained from the ERA5 reanalysis dataset Hersbach et al. (2020). These variables were spatially aggregated to the district level using the `xagg` package in R. District-level shapefiles were obtained from the GADM database of Global Administrative Areas, version 4.1 GADM (2023). From the processed temperature series, two agro-climatic indicators—Growing Degree Days (GDD) and Extreme Degree Days (EDD)—were constructed. These variables capture heat accumulation and extreme temperature stress, both of which are relevant for crop growth and yield variation Schwarzwald and Geil (2024); Kukal and Irmak (2018).

GDD was calculated using a base temperature of 10°C and a maximum cap of 35°C, following the methods of Roberts, Schlenker, and Eyer (2013) and Al Mamun et al. (2025). The formula is:

$$\text{GDD} = \begin{cases} 0, & \text{if avg\_temp} \leq T_b \\ \text{avg\_temp} - T_b, & \text{if } T_b < \text{avg\_temp} < T_m \\ T_m - T_b, & \text{if avg\_temp} \geq T_m \end{cases} \tag{7}$$

where $T_b = 10$°C and $T_m = 35$°C. Daily GDD values were aggregated to monthly totals.

EDD was used to quantify heat exposure above a harmful temperature threshold. It was calculated as:

$$\text{EDD} = \sum_{d=1}^{D} \max(T_d - T_{\text{threshold}}, 0) \tag{8}$$

where T_d is the daily average temperature on day d, $T_{\text{threshold}}$ is the extreme heat threshold set at 35°C, and D is the number of days in the month.

5. Theoretical Framework

In informal agricultural labor markets, wage contracts often include a mix of cash and in-kind components, particularly employer-provided meals. While this practice is widespread in South Asia and China, it remains under-theorized in empirical wage modeling. To guide our estimation strategy, we develop a theoretical framework that draws from two well-established approaches: the *efficiency wage theory*—specifically, its nutritional variant (Gupta, 1989; Bose, 1997)—and the *compensating differential theory* (Rosen, 1974).

5.1. Building on Existing Theories

Our framework combines key assumptions from prior theoretical work:

- Building on Rosen's model of hedonic pricing (Rosen, 1974), which treats goods as bundles of valued characteristics, we adopt the idea that compensation packages may include both monetary and non-monetary elements. Although Rosen focused on product markets, the same logic applies to labor contracts where non-wage benefits—such as meals—can offset cash wages. .
- From nutritional efficiency wage models (Gupta, 1989; Bose, 1997), we incorporate the assumption that meals enhance productivity by improving physical strength, endurance, or concentration.
- Following standard labor contract models, we assume workers only accept jobs that provide at least their reservation utility.

5.2. Contract Structure and Worker Utility

We model labor contracts as comprising two elements: a daily cash wage w and a fixed number of meals $m \in \{0, 1, 2, 3\}$ provided during the workday. Worker utility depends on the total value of compensation and any non-cash benefits associated with meal provision. The utility function is given by:

$$U(w, m) = u(w + p \cdot m) + h(m) \tag{9}$$

where:

- $u(\cdot)$ is a strictly concave utility function, $u' > 0, u'' < 0$,
- p is the imputed market value of one meal,
- $h(m)$ captures additional non-monetary benefits of meals—such as improved health, time savings, or reduced food insecurity—and is also concave: $h' > 0, h'' < 0$.

This formulation allows meals to act as both a cash-equivalent and a source of additional utility.

5.3. Employer's Objective and Efficiency Considerations

Employers select wage–meal combinations to maximize daily profit, accounting for the effect of meals on productivity. Let $e(m)$ represent the worker's effort level, which increases with meals but at a diminishing rate:

$$e'(m) > 0, \quad e''(m) < 0 \tag{10}$$

Daily profit is given by:

$$\Pi = A \cdot e(m) - (w + c \cdot m) \tag{11}$$

where:

- A is the marginal revenue product of labor per unit of effort,
- c is the employer's per-meal cost, which may be lower than the market value p due to informal sourcing or bulk cooking.

The employer must satisfy the worker's participation constraint:

$$U(w, m) \geq \bar{U} \tag{12}$$

where $\bar{U}$ is the reservation utility reflecting the worker's best alternative—such as casual self-employment or public employment.

5.4. Our Theoretical Contribution

This framework brings together two established mechanisms—compensating wage differentials and nutrition-based efficiency wages—within a single setting, adapted to rural agricultural labor where meals are provided in discrete quantities. It leads to several testable predictions that inform our empirical analysis.

- **Cash–Meal Substitution:** If meals have positive utility value, workers will accept lower wages when meals are provided. We expect the marginal effect of meals on wages to be negative:
$$\frac{\partial w}{\partial m} < 0$$
- **Diminishing Wage Discount:** Because the first meal likely has the largest marginal benefit in terms of effort and utility, we expect wage reductions to be-

come smaller with each additional meal:

$$\left|\frac{\partial w}{\partial m_1}\right| > \left|\frac{\partial w}{\partial m_2}\right| > \left|\frac{\partial w}{\partial m_3}\right|$$

where m_1, m_2, m_3 represent one, two, and three meals, respectively.

6. Result

6.1. Hypothesis 1: Yield Effects on Real Agricultural Wages

The results (Table 2) do not offer consistent evidence that higher agricultural productivity translates into higher daily wages. In fact, across most model specifications, the estimated association between rice yield in the previous year and real wages is negative. In the fully controlled specification—including district, year, growing season, and district-by-year interactions—a one-ton increase in the previous year's rice yield is associated with a reduction of approximately 12.7 BDT in the daily wage. This effect is statistically significant at the 5% level.

The negative relationship contradicts standard neoclassical expectations, where higher productivity raises the marginal product of labor and thus wages. One possible explanation is that in informal rural labor markets, gains in productivity are not always shared with workers. For instance, higher yields may reduce labor demand through shorter harvest periods, or may coincide with price drops that lower farm revenue and wage payments. Overall, the findings do not support the hypothesis that increases in agricultural yield translate into higher real wages for farm workers.

6.2. Hypothesis 2: Wage Adjustment through Meal Provision

Table 2 reports the effects of receiving meals on real wages, distinguishing between different quantities: one, two, or three meals per day. The omitted baseline category is workers who did not receive any meals.

The results consistently show that meal provision is associated with lower real wages, but the degree of wage adjustment varies by the number of meals. Workers receiving only *one meal* face the steepest wage discount—approximately 33 to 40 BDT less per day across specifications. For workers receiving *two meals*, the wage reduction is smaller, between 7 and 18 BDT. Interestingly, the coefficient on *three meals* is small, sometimes negative, but statistically insignificant or only marginally significant, indicating a minimal or uncertain wage discount.

These patterns suggest a diminishing marginal substitution between meals and wages. That is, the first meal appears to substitute substantially for cash wages, but additional meals contribute progressively less. This empirical result is consistent with theoretical expectations from efficiency wage and in-kind payment models.

Overall, the findings support Hypothesis 2: employers adjust monetary wages downward when meals are provided. However, the size of the wage adjustment depends non-linearly on the number of meals offered.

6.3. Hypothesis 3: Gender Wage Differentials

Across all model specifications (Table 2), male agricultural workers earn substantially more than their female counterparts. In the most saturated specification—including district, year, and season fixed effects, as well as district-by-year and district-by-season interactions—the estimated gender gap is approximately 111.6 BDT per day. This disparity is both economically large and statistically robust, persisting even after adjusting for observable factors such as rice yield in the previous year and meal provision.

Since the model accounts for variation in crop productivity, geographic and temporal factors, and in-kind compensation, the wage gap cannot be explained by these observed covariates. Rather, the consistent magnitude of the difference suggests that gender remains a salient and independent determinant of wage outcomes in rural labor markets. Potential mechanisms may include task-based sorting, differences in bargaining power, or social norms that undervalue female labor. These findings provide strong empirical support for Hypothesis 3, indicating that women are paid significantly less than men for similar agricultural work.

Table 1: Regression: First Stage (Corrected SE)

	Dependent variable:
	Change in Crop Yield
Growing Degree Days (GDD)	-0.001**
	(0.0003)
Extreme Degree Days (EDD)	0.188***
	(0.055)
Precipitation	-0.00001
	(0.0001)
GDD × Precipitation	0.00000
	(0.00000)
District FE	Yes
Year FE	Yes
Growing Season FE	Yes
District × Growing Season FE	Yes
Year × Growing Season FE	Yes
Clustered SE (District)	Yes
Observations	5,451
R^2	0.854
Adjusted R^2	0.840
Residual Std. Error	0.243 (df = 4977)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2: Wage Model with Meal Type

	Dependent variable:				
	Real Wage				
	(1)	(2)	(3)	(4)	(5)
Lagged Yield Hat	-0.092***	-0.041**	-0.031	-0.097*	-0.127**
	(0.019)	(0.019)	(0.019)	(0.051)	(0.056)
Gender (Male)	111.374***	111.809***	111.918***	111.628***	111.595***
	(1.380)	(1.350)	(1.346)	(1.191)	(1.187)
Meal Type: One	39.880***	32.332***	32.399***	33.186***	33.236***
	(2.231)	(2.629)	(2.621)	(2.309)	(2.297)
Meal Type: Two	18.429***	7.130**	7.478**	8.488***	8.758***
	(2.505)	(3.277)	(3.268)	(2.887)	(2.874)
Meal Type: Three	6.667**	-4.640	-5.505	-4.634	-5.013*
	(2.657)	(3.395)	(3.389)	(2.996)	(2.990)
Meal Type: No Info	36.305***	25.196***	24.404***	26.139***	25.873***
	(2.545)	(3.311)	(3.305)	(2.910)	(2.905)
District FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Growing Season FE	No	No	Yes	Yes	Yes
District × Year FE	No	No	No	Yes	Yes
District × Growing Season FE	No	No	No	No	Yes
Observations	5,172	5,172	5,172	5,172	5,172
R^2	0.749	0.760	0.762	0.840	0.846
Adjusted R^2	0.746	0.757	0.758	0.817	0.819
Residual Std. Error	47.004 (df = 5102)	45.983 (df = 5094)	45.851 (df = 5093)	39.923 (df = 4526)	39.718 (df = 4399)

Note: *p<0.1; **p<0.05; ***p<0.01

7. Future Work

7.1. Crop Expansion

The analysis will be extended beyond rice to include six major crops: Aus, Aman, Boro, Jute, Wheat, and Potato. Together, these account for approximately 93% of national agricultural output. District-level data on production, yield, and cultivated area—disaggregated by crop and variety—have already been collected from the *Yearbook of Agricultural Statistics* published by the Bangladesh Bureau of Statistics Bangladesh Bureau of Statistics (2014–2024), covering the period from 1970 to 2015.

Including additional crops will allow the study to test whether the relationship between yield and wages, and between in-kind incentives and cash wage adjustments, holds consistently across different agricultural systems, cropping cycles, and labor requirements. This expansion will strengthen the generalizability of the core wage model and help identify crop-specific drivers of rural labor demand.

7.2. Input Cost Structure and Labor Demand

For selected crops input cost components will be incorporated to better explain wage variation. These include the costs of land preparation, seeds, canal construction, irrigation, pesticide application, fertilizers, and harvesting. The total production cost per acre will be constructed as:

$$\begin{aligned}\text{Total Production Cost} = \ &\text{Land Preparation Cost} + \text{Seed Cost}\\ &+ \text{Canal Preparation Cost} + \text{Irrigation and Pesticide Cost}\\ &+ \text{Fertilizer Cost} + \text{Harvesting Cost} \qquad (13)\end{aligned}$$

Labor-related costs will also be disaggregated by production stage, including land preparation, seed sowing, canal construction, irrigation and pesticide use, fertilizer application, and harvesting. We hope this breakdown will help us understand how different phases of crop production influence the demand for labor and the structure of wage payments. By linking task-specific costs to wages, we aim to explore whether meals are used to replace part of the cash wage in more labor-intensive stages or if they follow other patterns in how employers compensate workers.

7.3. Seasonality and Cropping Patterns

A key extension of this study will assess how agricultural wages and meal incentives vary between lean and peak seasons. The goal is to understand if workers are paid differently, or more often given meals, during times when farming activity is low.

To do this, we will use crop calendar information from BBS's extension records to identify planting and harvesting months for major crops. This will help define which months are busy and which are lean. We will then match these seasonal periods with the monthly wage and meal data already collected. This step will allow us to track how wages and meals change across the year.

This analysis will show whether meals are more commonly offered when cash is limited or jobs are fewer, and how wage patterns change throughout the farming cycle.

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A. First Stage: Model Specifications

To estimate the impact of climate variables on yield, we tested different model specifications by sequentially adding fixed effects (FE) and interaction terms. Our approach can be summarized as follows:

- **Model 1:** A simple regression with no fixed effects:

$$yield = \beta_0 + \beta_1 gdd + \beta_2 edd + \beta_3 precip + \beta_4 (gdd \times precip) + \epsilon$$

- **Model 2:** Added **District Fixed Effects (FE)** to control for region-specific differences.
- **Model 3:** Included **Year FE** to account for temporal trends affecting yield.
- **Model 4:** Added **Growing Season FE** to capture seasonal variations.
- **Model 5:** Introduced the **District** $\times$ **Year interaction** to account for region-specific trends over time.
- **Model 6:** Included the **District** $\times$ **Growing Season interaction** to model how district-level characteristics vary across seasons.
- **Model 7:** Added **Year** $\times$ **Growing Season interaction** to analyze seasonal variations across different years.
- **Models 8-11:** Progressively added combinations of interactions:
  - Model 8: **District** $\times$ **Year** + **District** $\times$ **Growing Season**
  - Model 9: **District** $\times$ **Year** + **Year** $\times$ **Growing Season**
  - Model 10: **District** $\times$ **Growing Season** + **Year** $\times$ **Growing Season**
  - Model 11: Included all three interactions **(Full Model)**

Model Selection Criteria

Each model was evaluated based on:

- **Adjusted** R^2: Measures explanatory power while penalizing overfitting.
- **AIC (Akaike Information Criterion)**: Lower values indicate better model fit with fewer parameters.
- **BIC (Bayesian Information Criterion)**: Similar to AIC but penalizes complexity more strictly.

B. Model Diagnostic: First Stage

B.1. Multicollinearity Test

Multicollinearity arises when independent variables in a regression model are highly correlated, leading to inflated standard errors and unreliable coefficient estimates (Gujarati & Porter, 2009; Wooldridge, 2015). To diagnose multicollinearity, we employ the Variance Inflation Factor (VIF), a widely used diagnostic measure that quantifies the degree of linear dependence among explanatory variables. The VIF for an independent variable X_j is computed as:

$$VIF_j = \frac{1}{1 - R_j^2} \tag{B.14}$$

where R_j^2 is the coefficient of determination obtained from regressing X_j on all other explanatory variables in the model Kutner2004. The general rule of thumb states that a VIF greater than 10 indicates severe multicollinearity, while values between 5 and 10 suggest moderate concern (Gujarati & Porter, 2009).

Since our model includes District, Year, and Growing Season fixed effects, we first residualize each independent variable by removing these fixed effects using the within-transformation approach (Angrist & Pischke, 2009). Specifically, for each independent variable X, we estimate:

$$X_{i,t,s}^{resid} = X_{i,t,s} - \hat{X}_{FE} \tag{B.15}$$

where $\hat{X}_{FE}$ represents the fixed effects component estimated using a demeaned regression. After residualizing, we compute VIF values on the transformed variables using ordinary least squares (OLS), following the methodology by Fox (2016).

VIF Results

The VIF results for the independent variables in the fixed effects regression model (frist stage) are presented in Table B.3.

Table B.3: Variance Inflation Factors (VIF) for Independent Variables

Variable	VIF
Growing Degree Days (GDD)	1.08
Extreme Degree Days (EDD)	1.01
Precipitation (Precip)	1.85
GDD × Precipitation	1.77

The results indicate that all independent variables exhibit VIF values well below the standard threshold of 5, suggesting that multicollinearity is not a significant issue. The highest VIF value, 1.85 for Precipitation, remains within an acceptable range, confirming that the model specification does not suffer from excessive collinearity. The interaction term between GDD and Precipitation (VIF = 1.77) also falls within an acceptable limit (Kutner, Nachtsheim, Neter, & Li, 2004).

The Variance Inflation Factors (VIFs) for the independent variables used in the wage regression model are presented in Table B.4.

Table B.4: Variance Inflation Factors (VIF) for Second-Stage Wage Model Regressors

Variable	VIF
Rice Yield (Lagged)	1.25
Rice Yield (Current)	1.25
Gender (Male)	1.00
Meal Type: None	3.72
Meal Type: One	3.67
Meal Type: Two	3.53
Meal Type: Three	3.20

All VIF values fall well below the commonly used threshold of 5, indicating that multicollinearity is not a concern in this specification. While the meal-type dummies exhibit moderately higher VIFs (around 3 to 4), these are expected due to their categorical structure and do not pose estimation issues. These results affirm the stability and interpretability of the wage regression coefficients (Kutner et al., 2004).

B.2. Heteroskedasticity Test

Heteroskedasticity refers to a situation where the variance of the error term in a regression model is not constant across observations, which can lead to inefficient estimators and misleading statistical inferences (Gujarati & Porter, 2009; Wooldridge, 2015). To formally test for heteroskedasticity, we apply the Breusch-Pagan (BP) Test, a widely used diagnostic tool that assesses whether the residual variance depends on the explanatory variables (Breusch & Pagan, 1979; Pagan, 1980).

The null hypothesis (H_0) of the Breusch-Pagan Test states that the residuals exhibit homoskedasticity (constant variance), while the alternative hypothesis (H_1) suggests heteroskedasticity (non-constant variance). The test statistic is computed as:

$$BP = nR^2 \tag{B.16}$$

where:

- n is the number of observations.
- R^2 is the coefficient of determination from an auxiliary regression where the squared residuals are regressed on the independent variables.

Under the null hypothesis, the BP test statistic follows a chi-square (χ^2) distribution with degrees of freedom equal to the number of explanatory variables. A low p-value ($p < 0.05$) indicates evidence of heteroskedasticity (Fox, 2016).

Results

The results of the studentized Breusch–Pagan test for heteroskedasticity are reported in Table B.5.

Table B.5: Breusch–Pagan Test for Heteroskedasticity

Test Statistic (BP)	96.509
Degrees of Freedom (df)	6
p-value	< 0.0001

The test strongly rejects the null hypothesis of homoskedasticity, with a BP statistic of 96.509 (df = 6) and a p-value less than 0.0001. This provides compelling evidence that heteroskedasticity is present in the residuals. Accordingly, we employ cluster-robust and HAC-adjusted standard errors in all subsequent regressions to ensure valid inference.

Heteroskedasticity Adjustment

To address the heteroskedasticity and serial correlation detected in the residuals, we re-estimate the wage model using heteroskedasticity- and autocorrelation-consistent (HAC) standard errors based on the Newey–West estimator. This method adjusts the variance–covariance matrix to provide consistent standard errors under both forms of misspecification (?, ?; Wooldridge, 2015).

Table B.6 presents the coefficient estimates along with HAC-robust standard errors, clustered at the district level. The statistical significance of the key coefficients remains stable, confirming the robustness of our findings.

Table B.6: Regression Estimates with HAC-Adjusted Standard Errors (District Clustered)

Variable	Estimate	HAC Std. Error
Rice Yield (t-1)	-0.056	0.047
Male	111.63	13.13
Meal Type: None	33.20	1.18
Meal Type: One	8.50	4.04
Meal Type: Two	26.13	2.97
Meal Type: Three	-4.65	7.23

B.2.1 Test for Autocorrelation

The Durbin-Watson (DW) test is a statistical measure used to detect the presence of first-order autocorrelation in the residuals of a regression model. Autocorrelation occurs when the residuals are correlated across time, violating the assumption of independent errors in ordinary least squares (OLS) regression (Durbin & Watson, 1950).

The DW statistic is computed as:

$$DW = \frac{\sum_{t=2}^{T}(e_t - e_{t-1})^2}{\sum_{t=1}^{T} e_t^2} \tag{B.17}$$

where e_t represents the residuals of the regression model at time t, and T is the total number of observations. The DW statistic ranges from 0 to 4:

- $DW \approx 2$ suggests no autocorrelation.
- $DW < 2$ indicates positive autocorrelation.
- $DW > 2$ suggests negative autocorrelation.

Autocorrelation Results

The Durbin–Watson test yields a test statistic of 0.739 (p ¡ 0.0001), indicating strong evidence of positive first-order autocorrelation in the residuals. This violates the assumption of independently distributed errors and necessitates the use of HAC-robust standard errors to correct for autocorrelation.

B.3. First Stage: Model Comparison

Findings and Best Model

- **Models 6 and 10** provided the best balance between explanatory power and model efficiency.
- **Final Choice: Model 10**, will keep model 4 model 6 for robustness check.

Table B.7: Model Comparison Table

	R^2	Adj. R^2	AIC	BIC	District FE	Year FE	GS FE	District × Year	District × GS	Year × GS
Model 1	0.4484	0.448	3132.28	3171.91	No	No	No	No	No	No
Model 2	0.5852	0.58	1704.85	2160.51	Yes	No	No	No	No	No
Model 3	0.7785	0.7736	-1611.34	-805.68	Yes	Yes	No	No	No	No
Model 4	0.7806	0.7756	-1657.9	-839.03	Yes	Yes	Yes	No	No	No
Model 5	0.8369	0.7454	399.57	13356.11	Yes	Yes	Yes	Yes	No	No
Model 6	0.8362	0.8262	-2868.13	-787.95	Yes	Yes	Yes	No	Yes	No
Model 7	0.805	0.7944	-1982	-106.54	Yes	Yes	Yes	No	No	Yes
Model 8	0.892	0.8216	-1462.83	12755.01	Yes	Yes	Yes	Yes	Yes	No
Model 9	0.8607	0.772	-137.88	13875.25	Yes	Yes	Yes	Yes	No	Yes
Model 10	0.8537	0.8398	-3166.32	-29.55	Yes	Yes	Yes	No	Yes	Yes
Model 11	0.9085	0.8411	-2047.49	13226.95	Yes	Yes	Yes	Yes	Yes	Yes

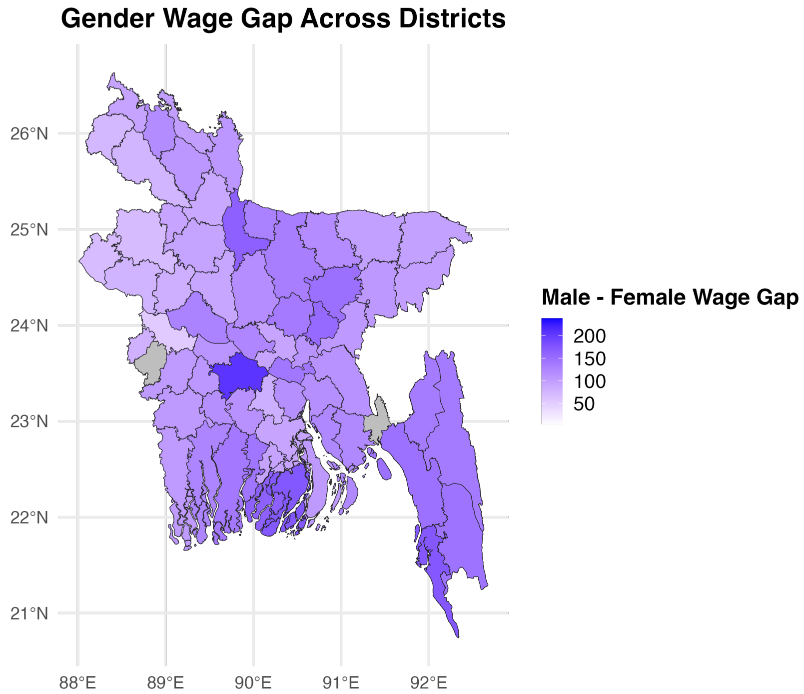

Figure C.1: District-level variation in the gender wage gap in agricultural labor. Darker regions indicate larger male–female wage differences.

C. Additional Figures

Figure C.2: Trends in average real agricultural wages across years. Wages adjusted for inflation.

Figure C.3: Real wage trends by gender and growing season. Male workers consistently earn higher wages across all seasons.

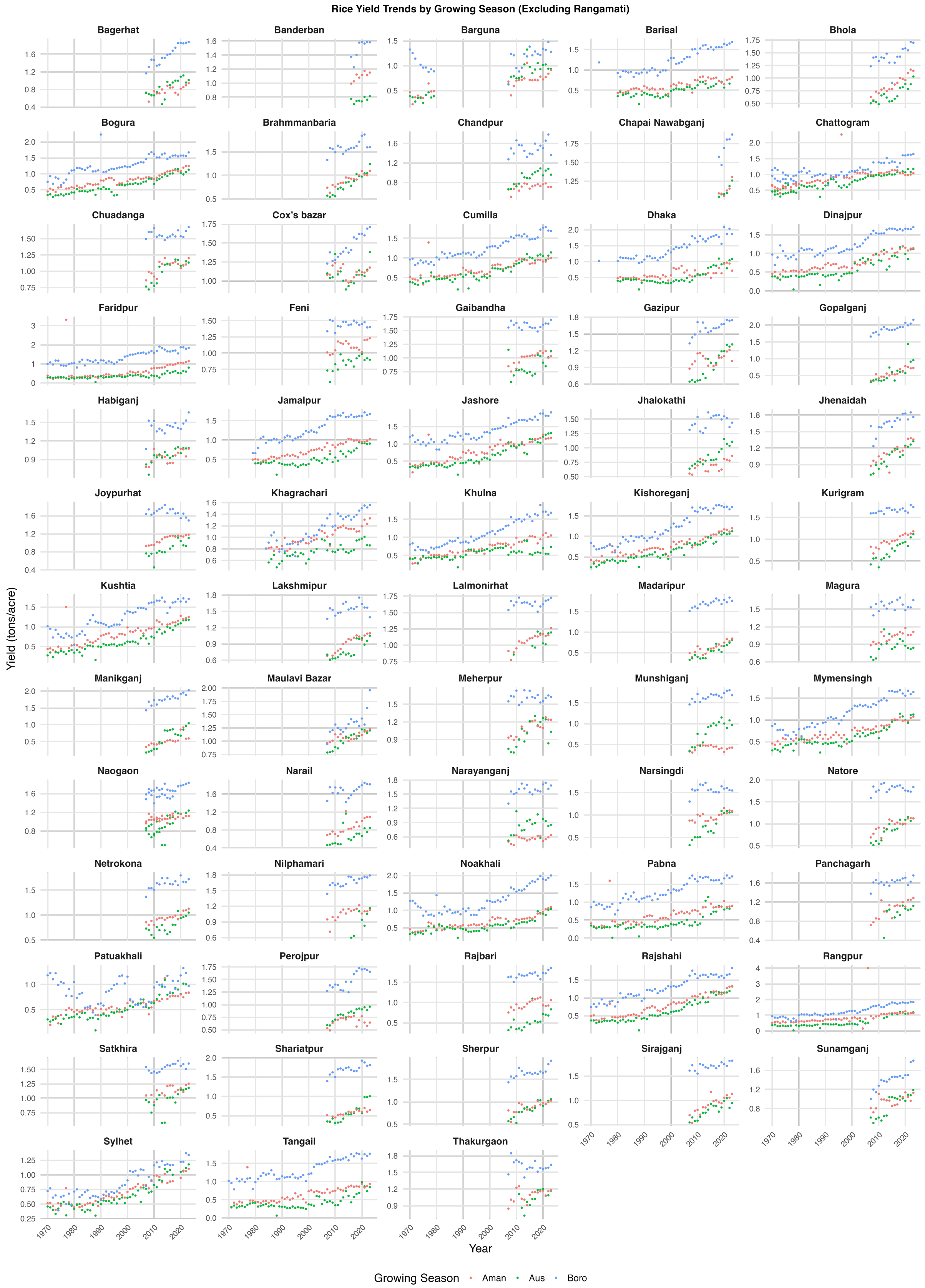

Figure C.4: District-level trends in rice yield across seasons. Each panel represents a different district.