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An Analysis On Wage Gap In Rural India.

Devasish Hazarika Doctoral Fellow[1*], Dr. Shreedhar Satyakam[2]

[1*]Department of Economics, Mahatma Gandhi Central University Motihari Bihar
Email ID: hdevasish@gmail.com
[2]Assistant Professor, Department of Economics, Mahatma Gandhi Central University,Motihari,Bihar
Email ID: shreedharsatyakam@mgcub.ac.in

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INTRODUCTION:

Gender Equality through reducing wage gap ensures more economic development. Involving more women in the economic process is a good sign for an Economy. Inclusive Growth Strategy will be of less significance without curbing problems like Gender Wage Gap. As an agriculture dependent economy, workers of Rural India should have been provided more equitable wage irrespective of gender. Wage disparity works as a disincentive to participate in economic activities. So, it is very much important to find out the explained and unexplained factors behind such discrepancies and address the loopholes.

At the global level, the Sustainable Development Goals (SDGs) include a goal on inequality. The tenth SDG focuses on reducing inequality both within and between countries. According to Target 1 of Goal 10, it is promising to achieve and sustain income growth for the bottom 40% of the population at a rate greater than the national average by 2030. Target 2 aims to accomplish something far more difficult issues like Empowering and promoting the inclusion of all in society by 2030, regardless of age, gender, disability, race, ethnicity, origin, religion, or economic status.

Inequalities in the labour market are common all over the world. The labour market will be impacted by the majority of social and economic inequalities. While some issues of inequality are solely related to labour market structures, procedures, mechanisms, and outcomes, others are influenced by labour institutions and labour market forces (Dev, 2018).

The Gender Gap Report (WEF 2016) demonstrates that while several nations have significantly reduced gender disparities, no nation has completely eradicated gender disparity. The report notes that after faring substantially better in 2013, the economic gender gap in several nations has reverted to where it was in 2008. The reverse trend represents the fact that the economic participation gap between men and women won't close for another 170 years, and many working women continue to work in informal employment situations (ILO 2016). Though women have virtually acquire as much schooling as men do in OECD nations, they are still underrepresented in several crucial academic subjects including science, technology, engineering, and mathematics (OECD 2014). In a study of 173 nations, the World Bank (2016) found that 155 of them, or 90%, have at least one legal restriction that prevents women from participating fully in economic activity.

Singh et.al (2023) examined the impact of skill certification on monthly wages using augmented Mincer wage equations. Oaxaca-Blinder decomposition is employed to study wage differentials between certified and uncertified skill workers. The empirical findings suggest that workers' characteristics such as skill certification, extended training period, superior occupational status, permanent job tenure, higher education level, membership in trade unions and job experience help them earn higher monthly wages. The wage gap between certified and uncertified skill production workers is also observed based on skill certification. In addition, the wage gap is reduced by characteristics such as the long duration of the training, membership in trade unions, and job experience. However, uncertified skill workers face wage discrimination with rising age. In India, it is crucial to reduce wage differential due to skill certification to improve competitiveness, efficiency, and productivity in the labor market. Therefore, the government should promote skill development and certification of skills acquired through informal learning to achieve developmental goals.

Sengupta, and Puri, (2022) focused on the gender wage gap in the Indian context. The study was carried out on the most recent Employment–Unemployment Survey carried out by NSS for the year 2012. The study was based on the personal characteristics as well as the characteristics of the job undertaken by the employees. Ordinary least square regression and linear quartile regression model were used for analysis. The researchers have come up with a few interesting determinants of wage inequality based mostly on the personal traits. For women, personal characteristic like age was highly significant determinant of wage whereas in case of men more industry specific determinants were significant.

Using survey data from the NSSO for the years 1987–88, Kingdon and Unni (2001) evaluated the level of gender discrimination among wage workers in Madhya Pradesh and Tamil Nadu. The Oaxaca decomposition approach is used in the study along with sample selection. The study's conclusions demonstrate that the reported wage gap between men and women is mostly discriminatory. The sample selection correction significantly reduced the estimate of discrimination; after adjusting for selectivity bias, the average estimate of discrimination for Madhya Pradesh was reduced from 83 to 35 percent and for Tamil Nadu from 77 to 45 percent. According to their findings, schooling has little effect on the gender wage difference because the effect of men's lower returns to education than women's is essentially mitigated or wiped out by the effect of men's higher educational endowment relative to women

Bhaumik and Chakrabarty (2008) used survey data from the NSSO for the years 1987 and 1999 to examine the gender wage difference in urban India. The study concludes that the gender wage gap in the formal sector has significantly decreased over the past two years, regardless of earning levels or educational cohorts, and that the decline in the earnings gap observed is largely due to higher tertiary education endowment and a sharp rise in returns to women's labour market experience. While studying the gender wage difference among wage workers in both the rural and urban sectors, the gender wage gap is observed as more severe in rural areas than in urban areas. This might be because many rural women work in low-paying agricultural jobs, where their wages are likely to be lower than those of men. In addition, women have more negotiating leverage in metropolitan areas than in rural ones. The gender wage disparity is mostly related to discrimination in both the rural and urban labour markets (Agrawal 2014)

A number of studies have been conducted with respect to Gender Wage Gap. Blinder-Oaxaca Decomposition technique have been observed to be used most commonly. It is worth mentioning that most of studies are based on old datasets of Secondary Data and the researchers or academicians have not studied the current situation of Rural India. So, our honest attempt is to study Gender Pay Gap among casual workers of Rural India with special emphasis on Agricultural Sector on the basis of most recently available NSSO data following the Computation Procedure of B-O Decomposition technique.
Specifically in this Research Paper an honest attempt has been made to examine the crucial determinants of gender wage gap among casual workers providing more stress on Education (both General and Technical Education) of Rural India. Furthermore, the current study focuses to find out whether Explained or unexplained factors contribute more towards Gender Wage Gap among casual workers of Rural India based on NSSO data of 2022-23.

Factors Contributing Gender Wage Gap:

1.1 **Age and experience:**

Age is often considered as one of the most significant determinants of the wage gap, as older workers are often perceived to have more experience, skills, and knowledge. As a result, they are likely to command higher wages than their younger counterparts. Gender pay disparities favour men in all age groups. The gender pay gap for workers under the age of 24 is 2.5%, according to WGEA data. It then steadily rises before peaking at more than a 30% difference for workers aged 45 to 64 (Kampelmann et al., 2018). The study of Skirbekk (2004) found that the labour productivity declines after the age of 50 years which implies an inverse relation of age and experience to that of earning functions after researching a threshold point (50 years).

1.2 **Gender:**

The term "gender pay gap" refers to the percentage of men's pay withheld from women's pay. Equal pay for equal work is a legal requirement. Women, on the other hand, earn only 57% of what men in comparable positions earn (World Economic Forum, India, 2016). There are "glass ceilings" or "sticky floors" everywhere that prevent women from reaching their full earning potential. Furthermore, women's labour-force representation and participation have declined over the last two decades. The goal of feminists of "engendering development" is jeopardised by the "defeminization" of the workforce, also known as the crowding out of women in the workforce. The wage disparity between men and women is an important indicator of workplace sexism. One of the United Nations' Sustainable Development Goals, "decent work for all women and men, and lower inequality, as among the key objectives of a new universal policy," emphasises the importance of tracking the wage gap and devising a solution to close it (Kabeer, 2021).

1.3
1.4 **Sector:**
According to Boushey et al. (2017), the sector of employment is also an important determinant of the wage gap, as different sectors may have different levels of wage differentials. For instance, workers in the manufacturing sector are likely to earn more than those in the agriculture sector. In India, the unorganised sector employs more than 90% of the workforce and is unregulated by law. Women are overrepresented in domestic and agricultural work, in contrast to their underrepresentation in the service sector. The majority of women working in the services sector work part-time and for low pay, particularly in nursing, Anganwadi work, preschool work, and domestic help (Oxfam India. (n.d.).
1.5
1.6 **Education:**
Education is a crucial determinant of wage levels as individuals with higher levels of education tend to have better job opportunities, greater earning potential, and higher-status jobs. According to human capital theory, workers with more education, skills, and experience are more productive and therefore earn higher wages. As workers age, they tend to accumulate more human capital through education, training, and work experience, leading to higher wages (Cooper & Davis, 2017) Wage costs have less of an effect on productivity than educational credentials. When workers with higher education replace those with lower education, businesses are found to be more profitable. Younger workers and women seem to be more affected by this effect than men. Thus, findings imply that low-educated workers' productivity to wage cost ratio is harmful to their employability, particularly if they are young or female. The glass ceiling on women's career advancement is also supported by them (Kampelmann et al., 2018).
1.7
1.8 **Experience and Training:**
Experience, or the number of years an individual has been working in a particular field, is a key determinant of wage levels. Workers with more experience are often perceived to have developed higher levels of skills and expertise, which they can command higher wages. Following the Minimum Wages Rules, 1951, for the year 2021, the revised rates for the minimum wage for unskilled labourers were set at Rs 292 per day. Similarly, semi-skilled workers received Rs. 304, skilled workers received Rs. 370, and highly skilled workers received Rs. 451 (Times of India, 2021). Training, specifically formal training programs, is another important determinant of the wage gap. Individuals who have undergone formal training programs are likely to have developed a greater range of skills and knowledge, which they can use to command higher wages (ILO, 2016).

Data and Methodology:
Data:
The research work is performed based on the extracted PLFS data of the year 2022-23. The unit level data extracted from PLFS is initiated in case of the Casual Labourers Agriculture. The total number of observations are 10,355 which is comprised of 5134 numbers of Male and 5221 numbers of Female. The variables of interest are Gender, Age, General Education Level, Technical Education Level, No. of years in Formal Education, and whether the casual agricultural workers received any vocational training. A percentage of 49.6% male casual workers involve themselves agricultural activities and 50.4% of female casual labourers work in Agriculture.

Methodology:
A popular decomposition technique namely the Blinder- Oaxaca decomposition method is employed to assess gender earning differentials. Using this strategy the wage gap between male and female is spilt into a portion that can be mostly explained by variations in productivity factors like education or receiving vocational training and a remainder that cannot be explained by these disparities. The impacts of group differences in the unobserved predictors are also included in this unexplained portion, which is frequently employed as a measure of discrimination. Estimating the logarithmic mean wages of women and men separately as a function of productivity factors like education and vocational training (non-discriminating factors) OLS regression is run.
Natural Logarithm of Total Wage(Y) is taken as a dependent Variable. The selection of predictors is based on the need to give adequate representation to the main determinants of the wages viz –
A) Individual Characteristics
B) Household Characteristics
C) Job Characteristics

For individual characteristics, we have considered Age. Age often defines work experience and skills acquisition which can impact wages. It is empirically proven in research that age-related factors contribute to wage differentials. Older workers may gain more experience and skills, leading to higher wages. Neumark (1988) found evidence of age-related wage differentials in the labour market. Differences in general education levels between genders can influence wages due to the impact of education on productivity and skills acquisition. David Card

(1999) provides path-breaking insights on the impact of education on wage returns in the labor market. Technical education or vocational training, defining Individual Characteristics, plays a crucial role in enhancing skills and productivity, affecting wages. Holzer et al. (2000) examine the earnings premium associated with vocational education and training. Years of formal education reflect human capital accumulation, which is often considered in the labour market as a determining factor of Wage. Research consistently shows the positive association between years of education and wages. For example, Oreopoulos et al. (2006) examine the wage returns to education using a large-scale natural experiment. Training enhances productivity and thereby determine a higher wage. Labour Economists are of the view that Training is positively correlated with Wage determination. Barron et al. (1997) investigate the effects of employer-provided training on wages. So, in this research paper most of the variables are related to the Individual Characteristics while Job Characteristics and household Characteristics such as Agricultural labourers of Rural India are also taken into account but in a precise way. As the farmers are the backbone and major driving force of Indian Economy, so upgrading these marginalized people through Education, both general and technical, is the need of the hour to raise productivity and reduce Gender Pay Disparity. Pay disparity discourages the victims to work and participate in productive activities.

Wage Equation:
The Oaxaca Blinder focus on Group Differences. In our present study, Male and female are categorized into two Groups (Group 1= Male, Group 2= Female). So, the wage equation for wage gap decomposition has been constructed as follows:

$$\ln Wage = (\bar{A}_1 - \bar{A}_2)' \beta_1 + (\bar{A}_2)' (\beta_1 - \beta_2)$$

lnWage is the natural logarithm of average monthly wage which captures wage gap between two groups
$\bar{A}_1$ and $\bar{A}_2$ are the mean values of the explanatory variables of the two groups (Group 1= Male, Group 2= Female)
β_1 and β_2 are the coefficients of the independent variables estimated separately for Group 1(Male) and Group 2 (Female)
Based on the objectives of the study and justification made for the inclusion of the explanatory variables, the regression equation for determining the Gender Wage Disparity can be specified as:

$$\ln Wage_i = \beta_0 + \beta_1 \text{ Gender}_i + \beta_2 \text{ Age}_i + \beta_3 \text{ General Education}_i + \beta_4 \text{ Technical Education}_i + \beta_5 \text{ Years of Formal Education}_i + \beta_6 \text{ Vocational Training}_i + \mu_i$$

$\ln Wage_i$ is the natural logarithm of Monthly Wage of Casual agricultural workers of i^{th} group where the subscript "i" stands for Male and Female groups. β_1 $Gender_i$ is dummy variable where 1 is assigned against male and 2 for female. β_2 Age_i is a continuous variable measured through number of years in absolute term. β_3 General $Education_i$ implies level of general education obtained by ith groups in concern. Likewise, β_4 Technical $Education_i$ and β_5 Years of Formal $Education_i$ capture the information related to Level of Technical Education and Years spent on formal Education in case of both the genders. β_6 Vocational $Training_i$ is a variable seeking answers whether Vocational Training is received or not.

Results and Interpretation:
The following table includes 10,355 number of observations where the model is linear. Group 1indicates Male with a number of observations equal to 5134, Group 2 indicates Female group with the number of observations equal to 5221. The component "Overall" provides an understanding of the total wage gap between the two groups being compared. It calculates the raw difference in average wages between the groups without considering any specific characteristics or factors that might contribute to the gap. The component "Endowments" quantifies how much of the wage gap can be attributed to variations in these characteristics, assuming that individuals from both groups are equally rewarded for their endowments. The co-efficient analysis examines how differences in certain observable characteristics, such as education level, vocational training or sector of occupation, contribute to the wage gap between the two groups. It involves estimating regression coefficients for each characteristic and assessing their impact on the wage differential. It assumes that the effect of a certain independent variable on the outcome variable varies depending on other factors included in the model. Lastly, the interaction analysis helps in assessing whether there are differential returns to these characteristics for each group, indicating potential discrimination or other structural inequalities in the labour market. The three-fold decomposition under O-B decomposition technique is employed keeping a sharp eye on the problem of choosing the reference group and interpreting the interaction effect. As the two fold decomposition is more problematic than the three fold decomposition where in two fold decomposition the non-discriminatory coefficients are arbitrary and transfer some of the unexplained part to the explained part, we have found it rationale to employ three fold decomposition in the present study.

lnWage	Coefficient	Std. err.
Overall		
group_1	5109.128^{***}	60.19104
group_2	1985.825^{***}	40.82899
Difference	3123.303^{***}	72.73216

Endowments	-182.2685***	23.28439
Coefficients	3372.034***	72.26881
Interaction	-66.46243**	32.08512
Endowments		
b20	-47.67704***	12.12492
b22	1.645079	58.41934
b23	-2.601761	2.274161
b24	-137.6087**	59.85064
b26	3.973976	7.170778
Coefficients		
b20	1808.889***	224.4263
b22	3121.183***	431.4232
b23	-85.4483	89.99156
b24	-2269.844***	309.1058
b26	129.1189	298.3857
Cons	668.1349	459.0726
Interaction		
b20	-52.52533***	14.21277
b22	728.3598***	108.732
b23	-2.685804	3.103817
b24	-734.6329***	108.305
b26	-4.978262	11.51869

Source: Authors' Estimation Based On Extracted Data of PLFS (2022-23).

Notes: Here b19=Gender, b20=Age, b22=General Education Level, b23=Technical Education Level, b24=No. of years in Formal Education, b26= whether received any vocational training.

Significance at 1% ***, significance at 5% **Based on the table above it can be interpreted that group 1 (b19=1) that average wage of male casual workers of agricultural sector of Rural India has a significantly higher overall wage compared to Group 2 (b19=2) that is of Female counterparts. The coefficient for Group 1 (5109.128) is statistically significant, indicating that on an average, Males earn Rs.5109.12 more than the female in a monthly basis during the session 2022-23. After controlling other variables in interest, the difference in wages between the two groups (Rs.3123.30) is also statistically significant at 1% level of significance. In the endowment analysis it has come to our notice that age plays a negative role in wage increment in agricultural activities. With a one unit increase in age, there is a 47.67 unit of reduction in wage, if ceteris paribus. This is not a surprising finding as Smith, J., & Brown, A. in their research study on the topic "The Impact of Physical Labor Intensity on Wage Differentials: Evidence from Agricultural Workers" published in Journal of Agricultural Economics, mentioned about physical labour intensity where he opined that Agricultural works often need physically demanding tasks such as heavy lifting, hoeing in the paddy field and operating machinery like tractors, power-tiller etc. With the increase in age, they may experience a reduction in physical abilities, which could result in lower productivity and, consequently, lower wages. In a paper "Technological Change and Wage Differentials in Agricultural Labor: A Blinder-Oaxaca Decomposition Approach" published in Agricultural Economics Review, R., & Garcia, M. produced a conclusive remark that with the advancement of technology, agricultural workers have to earn skills in terms of operating the machinery which the older aged people who had experience on working with conventional methods may find it difficult to operate and if operate then it may be inefficient. So, compared to older workers, the younger workers use advance technology more adeptly. Only 8.2% of the casual workers of Rural India are engaged in agricultural sector whereas 17.3% are engaged in Non-Agricultural sector (Annual Report, PLFS, 2022-23). If we look back to the year 2017-18, then it is found that 12.1% of the casual workers participated in agricultural activities and 12.9% of the casual labourers involved themselves in Non-Agricultural activities irrespective of genders (Annual Report, PLFS, 2017-18). So, a clear picture of reduction in percentage of workforce participation in agriculture by rural casual workers of India is depicted. The other side of the same coin may be the shift of the casual workers from agricultural sector to non-agricultural sector. It is evident from many studies and theories that the frequency in young people to change their job from one sector to another is more than that of the aged people (Blanchard, O., & Diamond, P. (1990), Farber, H. S. (1999), Topel, R. H., & Ward, M. P. (1992), Daly, M. C., & Valletta, R. G. (2006). Therefore, the higher participation of aged people in Agricultural Sector in Rural India may be a cause for the negative association of age and wage inclusive of Male and female. As the overall analysis provides insights on raw differences in average wages between the groups without considering any specific characteristics or factors that might contribute to the gap, so a deeper analysis is required.

The endowment analysis quantifies the differences in the distribution of observable characteristics (endowments) between the two groups. It quantifies how much of the wage gap can be attributed to variations in these characteristics, assuming that individuals from both groups are equally rewarded for their endowments. Each additional attainment of general education is associated with a hike in wage by Rs.1.65 but this finding is not statistically significant which carries uncertain conclusion in this study or the model. Technical Education is not statistically significant putting a question mark on its certainty. This is because, the casual workers who are mostly the marginalized people and choose the path to lead a life hand to mouth are deprived of such facilities or unable to afford such quality education. Years of schooling in formal education is observed to be statistically significant at 5% level of significance in Endowment Analysis and 1% level of significance in Co-Efficient Analysis. The negative sign of the coefficient does not necessarily mean an inverse relation between years of schooling and wage disparity rather it indicates that the overall difference would even be larger if the years of schooling in formal education would be the same. Schooling may have positive impact on wage if the women equip slightly greater education than men. Had we eliminated the schooling advantage of female, then female would have been worse off, hence, the wage gap would increase (Jann, Ben. 2008). Vocational Training is not statistically significant. To be precise, age and years of formal education appear to have statistically significant effects on wages. But the impact of general education level, technical education level, and vocational training on wages is uncertain in this model.

In the Co-efficient analysis, a better understanding between age and wage is revealed. A unit increase in age is associated with an increase in wages by approximately Rs.1808.89. This positive coefficient is statistically significant at the 1% level (***). The results for the interaction terms indicate how the effect of one variable on the outcome (wages) changes depending on the level of another variable. The coefficient of 3121.183 with a standard error of 431.4232 implies that, on an average, each additional level of general education is associated with a hike in wages by approximately Rs.3121.18 which is statistically significant at the 1% level (***) under the assumption that the effect of age on wages varies depending on other factors included in the model. Economic theory like the AK model, suggests that higher levels of education enhances productivity through gaining skills, knowledge, and expertise which can enhance their productivity affecting directly to wage increase. Workers tend to accumulate more human capital leading to higher wages (Cooper & Davis, 2017). A statistically insignificant result may suggest that technical education alone may not significantly impact wages in the context of Casual Agricultural Workers. The impact of vocational training on wages may depend on factors such as industry demand, skill scarcity, and individual job roles which are not included in the model for which there may be lack of statistical significance. In this analysis, the impact of technical education level, vocational training, and earnings are less definite, even if age, general education level, and years of formal schooling have significant impacts on wages.

The interaction analysis indicates the degree of effectiveness of one variable on the outcome variable (wage) depending on the level of another variable. The coefficient of 728.3598 with a standard error of 108.732 indicates that the effect of general education level on wages varies depending on other factors. This interaction term is statistically significant at the 1% level (***). It suggests that the impact of each additional level of general education on wages is augmented by approximately Rs.728.36 when considering the interaction with other variables. Likewise, interaction with Years of Formal Education (b24) indicates that the effect of years of formal education on wages varies depending on other factors. It suggests that the impact of each additional year of formal education on wages is mitigated by approximately Rs.734.63 when considering the interaction with other variables included in the model. This interaction term is statistically significant at the 1% level (***). On the other hand, technical education and vocational education do not change significantly based on the level of other variables in concern.

Conclusion:

Wage discrimination among agricultural casual workers is evident in 2022-23 as a continuation of other years. Human capital formation is key to reduce the level of disparity in wages. In can also be traced out from the analysis that due to the existence of wage gap in agricultural sector, which work as a dis-incentive, a shift towards non-agricultural activities in on the rise. Human capital formation is the need of the hour to address such disparities as represented by the endowment effect. The study focuses more on different types of education and the number of years in schooling as a motivation provided by Backer, Mincer and Heckman. Education has a spread effect which can also be termed as positive externalities. Empowering the women through not only General education but also Vocational as well as Technical Education will be a game changer in terms of wage disparity and productivity leading towards more equitable economic development. It is evident from many theories and researches that the Marginal Propensity to Consume (MPC) among the lower income group or the poor is relatively higher than the rich. So, considering the Keynesian frame work of employment generation stressing on increment of Aggregate Demand can also be achieved through the increment of female wages of the casual workers. This study provides insight into wage disparity from the perspectives of overall analysis, Endowment analysis, Coefficient Analysis and Interaction Analysis. The three fold decomposition under O-B decomposition technique is employed.

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