Evaluating the Impact of Skill Development Initiatives on the Wages of Construction Workers: A Case Study in Assam

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Abstract

The Assam Building & Other Construction Workers' Welfare Board initiated a Skill Training Program (STP) to enhance the capability of registered construction workers, aiming to boost their skills, income and job prospects. This study investigates the impact of the STP on construction workers in terms of wages from 13 districts in Assam covering occupations like plumbing, carpentry, masonry, electrical and painting. The central emphasis of the study revolves around determining whether there has been a rise in wages subsequent to the implementation of the STP. The findings reveal a significant rise in wages among trainees compared to non-trainees, with notable variations across occupations. Painters and plumbers experienced the highest wage gains, while masonry workers showed no significant improvement examined using Difference in Difference (DiD) method. Regression results further confirm that the program effectively boosts wages and enhances real purchasing power, with trainees'current (2023) wage exceeding inflation-adjusted wages. The study also highlights disparities based on gender, religion, social groups, and education, emphasizing the dynamic nature of wage determination.

Introduction

The Indian construction industry plays a pivotal role in the national economy, contributing significantly to GDP and employment. As one of the largest employers in the country, it

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sustains millions through job creation, with an estimated 50 million workers employed in the sector (Gandhi et al., 2013). The construction sector's market size is projected to grow substantially, reaching an estimated Rs. 2,48,000 crores by 2025, and positioning India as the third-largest construction market globally (Ahuja et al., 2020). Given its contribution to both economic growth and employment, particularly in states like Assam, the sector's importance in national development cannot be overstated. In Assam, for instance, the number of workers employed in construction increased from 6.62 lakh in 2011 to 8.66 lakh by 2018, accounting for nearly 50% of the state's total employment (Hira, 2021).

Despite the sector's critical role, challenges related to productivity, efficiency, and quality persist. One of the main issues plaguing the construction industry is the shortage of skilled labour, which exacerbates inefficiencies and delays in construction projects (Agrawal and Agrawal, 2017; Wang et al., 2008). While advanced technologies have the potential to improve productivity, their high initial costs and limited access in developing nations hinder their widespread adoption (Durdyev and Mbachu, 2017; Ofori, 2007). Consequently, the construction industry in India remains heavily reliant on manual labour, with workers often lacking the necessary technical skills to meet the evolving demands of the sector.

In this context, training programs, particularly Skill Training Programs (STP), have become essential in enhancing the competency of workers. These programs are crucial for equipping workers with the necessary technical and vocational skills, thereby improving their job prospects and overall competitiveness in the labour market. Furthermore, STPs play a significant role in improving workplace safety, as workers trained in hazard recognition tend to contribute to safer work environments, thereby reducing the risk of accidents and injuries (Noghabaei & Han, 2020). These programs not only enhance job retention but also improve overall job satisfaction, leading to higher long-term earnings (Froyland & Terjesen, 2020). Moreover, vocational training is particularly beneficial for dislocated workers, as it increases their chances of reemployment in better-paying positions (Tang, 1993).

While the benefits of training on productivity and safety are well-established, the impact of such training on wage outcomes has received less attention. This research aims to address this gap by exploring whether the STP contributes to an increase in the real wages of trained construction workers. This research contributes to the literature by providing empirical evidence, specifically examining the effects of STPs on wage outcomes for construction workers in Assam. It evaluates whether trained workers experience real wage increases, taking into account socio-economic factors.

Skill Enhancement and Upgradation by ABOCWWB

Given the pivotal role of construction workers in the infrastructural progress of emerging and developing economies, the emphasis on their education and training cannot be overstated. Therefore, to address these challenges, the government and various stakeholders have introduced various programs at the national and regional levels. At present, India has three different training schemes to provide skills to construction workers. These are the Craftsman Training Scheme (CTS), Apprenticeship Training Scheme (ATS), and Skill Development Initiative Scheme (SDIS). The SDIS is the most recent and advanced training scheme for workers in India. Under the SDIS, training is imparted for more than 90 trade disciplines (occupations), which is far larger than the previous training schemes (Johari & Jha, 2019). Through these, workers are immersed in comprehensive training modules, culminating in the acquisition of skill certificates that validate their expertise. Such initiatives are not merely about addressing skill gaps but are fundamental steps toward dignifying the profession and ensuring sustainable growth for the construction workforce. In short, the goal is to empower them, enhance their job prospects, and ensure their overall welfare. On a similar note, a similar initiative was led by the Assam Building and Other Construction Workers Welfare Board (ABOCWWB), whereby Government of Assam initiated a Skill Training Programme (STP) in the year 2018-19 in two phases covering 30 districts of Assam. STP was an attempt to ensure better work opportunities and wage-earning sources for registered construction workers.

The Government of Assam constituted the ABOCWWB in 2008. One of the features of the Act is to create a welfare fund whereby benefits are open to all registered eligible construction workers. These include medical assistance, maternity assistance, death benefits, funeral assistance, marriage assistance, educational scholarships to the children of registered construction workers, loans, general, disability and family pensions, job oriented technical and vocational training to the eligible children of the registered construction workers with skill development training for the eligible registered construction workers. The Government of Assam under this board initiated the skill training program for the registered workers who got skill-based formal training and received a skill certificate after successful completion of the training. The skill development initiative is implemented through a well-designed format whereby training and assessment partners along with industry partners are involved in providing the requisite skill training. The overall architecture for this skill enhancement process includes four steps: Assessment, Skills Training, Final Assessment and Certification, and Tracer Study.

The STP was initiated in two phases. The first phase was initiated covering 13 districts of Assam: Barpeta, Nalbari, Baksa, Chirang, Bongaigaon, Darrang, Kamrup, Dibrugarh, Tinsukia, Dhemaji, Sivasagar, Jorhat and Udalguri. In the second phase, the remaining districts were covered under the Programme with 99 training centres utilised by 13 training partners selected for the purpose. However, the study is completely based on the first phase of the program.

A total of 30607 construction workers are registered for the STP out of which 28118 (92 percent) completed the programme. The STP programme was launched with a duration of two months in each of the districts under both phases with eight (8) hours of training sessions per day. The trades (occupations) included under the STP are plumbing, masonry, painting, carpentry, bar bending, and electrician. Each of the participants of the STP was provided with a stipend of Rs 280 per day (subject to a minimum attendance of 50% i.e., 30 days).

Literature Review on the Determinants of Wage Rates

The determination of wage rates is a central issue in labour economics, influencing both policy decisions and labour market efficiency. Various factors, including individual characteristics, institutional frameworks, and macroeconomic conditions, shape wage rates. This literature review examines the primary determinants of wage rates, offering insights from microeconomic and macroeconomic perspectives, with key theoretical frameworks and empirical findings.

The neoclassical theory of labour markets highlights supply-side factors, emphasizing that wages are determined by labour supply and demand. According to this theory, wages reflect workers' skills, education, and experience. The human capital theory (Becker, 1964; Mincer, 1974) extends this view, suggesting that investments in education and training enhance productivity, leading to higher wages. Wage disparities arise from differential investments in human capital, with more educated or skilled workers commanding higher wages. However, the theory has been critiqued for overlooking issues such as wage inequality, unemployment, and discrimination, which led to the development of alternative models (Leontaridi, 1998).

Segmented labour market theory (Leontaridi, 1998) challenges the neoclassical model by introducing labour market segmentation. It argues that labour markets consist of distinct segments with different rules, often influenced by institutional and social factors. Certain segments may disproportionately reward specific skills, while others offer limited access to well-paying jobs despite similar qualifications. This theory emphasizes the importance of institutional and structural factors in wage determination and suggests that segmented labour markets perpetuate wage inequality.

Recent empirical studies also highlight the influence of personal characteristics and socio-political factors on wage outcomes (Bhattarai, 2017). International perspectives on wage determination have been explored by Perry et al. (1975), who noted significant wage variations across countries due to both domestic factors and global conditions like foreign trade. Their research, building on William Nordhaus's work, found that no single theory could explain wage behavior across all nations, underlining the need to consider both local and global factors when analyzing wage rates.

Labour market dynamics are shaped by broader economic conditions, including demographic trends and labour market mobility. Sarycheval& Shvetsov (2015) analyzed the relationship between labour supply and demand, highlighting how aging populations are leading to labour shortages in certain sectors. Their study emphasizes the need for a rational distribution of labour and greater workforce mobility to address these imbalances. By using regression models with panel data, they assessed the effects of various factors on labour market trends, providing insights into structural factors that influence employment and wage outcomes at national and regional levels.

Another key approach to wage determination is the earnings function model, which regresses wage rates on personal, market, and environmental variables. Willis (1986) offers a comprehensive review of this model, which has been used to study issues like wage discrimination and the impact of education and training on wage outcomes. The human capital earnings function, in particular, has been pivotal in understanding how investments in education and training influence wages over an individual's career. This approach has been central in testing wage determination theories and providing empirical evidence of the significant role of education in explaining wage disparities.

Methodology and Analytical Framework

Sampling Methodology

This study is conducted across 13 districts of Assam namely Barpeta, Nalbari, Baksa, Chirang, Bongaigaon, Darrang, Kamrup, Dibrugarh, Tinsukia, Dhemaji, Sivasagar, Jorhat and Udalguri, aiming to address crucial inquiries by gathering insights from both registered trainee and non-trainee construction workers through a carefully designed sample survey. The study involves 1890 registered construction workers, chosen from a total pool of 30,607, with a 2% margin of error and a 95% confidence interval. The sample is stratified into two groups: 945 trainee workers and 945 non-trainee workers for the primary survey[3], which is carried out through a randomized control experiment spanning a variety of occupations including plumbing, carpentry, masonry, electrical, bar bending, and painting.

To ensure equitable representation of workers across districts, the sample is distributed proportionately to the total number of registered workers in each district. Mitigating potential bias, sample units are randomly selected without replacement, allowing for flexibility in cases where a particular unit is unavailable or unwilling to participate in the survey. This approach is undertaken to enhance the reliability and comprehensiveness of the study's findings.

Analytical Methodology

The study utilises two distinct approaches to examine the impact of STP on the wage rate of workers. In the first approach Difference-in-Differences (DiD) technique is used which delves into the program's impact on wages. In the second approach, two regression models are used to examine whether the change in wage rate after a period of time (4 years) aligns with inflation or not.

Difference in Difference Approach

Initially, 1075 observations are collected for each group: trainees and non-trainees. However, within 4 years, a majority portion of individual shifted their occupations.

[3] Statistically the estimated sample beneficiary size (with the above-mentioned configuration vis confidence interval, margin of error and sample proportion) is 1890 (945 trainee beneficiaries and 945 non-trainee workers respectively). However, in order to enhance the certainty and reliability of the research outcomes, the number of beneficiaries are purposively increased to 2150: 1075 trainee beneficiaries and 1075 non-trainee workers respectively.

Although this shift is not largely different from the previous occupations[4] but the wage rate somehow is different for each occupation. Hence, the wage rate of two different occupations in two different time intervals cannot be compared to assess the change. Thus, only those observations having the same initial and current occupations at the time of the survey are taken into consideration. To examine, a total of 199 individuals for each group (199 trainees and 199 non-trainees) are filtered out. Due to two time periods (before and after), the final observations become double. In the final stage, 398 observations are gathered for each group (398 trainees and 398 non-trainees).

Counterfactual trend analysis for a DiD (Difference-in-Differences) is a statistical method used to estimate the causal effect of a treatment or intervention by comparing the change in outcomes over time between a treatment group and a control group. The basic idea is to estimate what would have happened to the treatment group in the absence of the intervention and then compare it to what happened with the intervention. The formula for the Counterfactual outcome of the treatment group in a Difference-in-Differences (DiD) analysis is:

Counterfactual outcome of treatment group = Pre-treatment Outcome of Treatment Group -Observed Change in Control Group.

1. "Pre-treatment Outcome of Treatment Group" represents the average or observed outcome of the Treatment Group during the period before the treatment or intervention.
2. "Observed Change in Control Group" represents the change in the Control Group's outcome from the pre-treatment period to the post-treatment period.

This formula represents the counterfactual scenario by assuming that, in the absence of the treatment, the outcome of the treatment group would have followed the same trend as the outcome of the control group.

Regression Models and Variable Specification

The Difference-in-Differences (DiD) model examine if there are any differences between daily wages of trainee and non-trainee workers after STP. However, it is crucial to note that wage rates are influenced not only by skill levels but also by broader economic factors such as inflation, productivity, and the supply and demand for labour. Capturing all these external factors simultaneously is difficult. In this study, inflation is specifically considered to examine an alternative scenario that adjusts the wage rates for inflation, assessing whether the increases in wages for both trainee and non-trainee workers are meaningful after accounting for inflation. The findings from previous empirical studies show that the real wage gap between workers in the public and private-informal sectors is significant, with informal sector workers earning 3.8 times less (Glinskaya and Lokshin, 2007). Furthermore, there is a lack of monitoring and enforcement of minimum wage laws in the unorganized sector, and anecdotal evidence suggests that

[4] Different occupation implies someone who initially was a mason or other construction worker and later works as painter or plumber etc. .

minimum wage standards are rarely followed. Within this sector, the most significant factor determining wages is productivity, which shows the strongest correlation with wage levels.

To evaluate whether STP training has helped construction workers secure better wages and if the current wages (2023) align with inflation, two regression models were employed in the study.

1. First Model:

Dependent Variable: Monthly wage rate of all construction (Trainee+ non-trainee) workers.

Null Hypothesis (H_0):STP training does not have a significant effect on improving wages across the workforce.

2. Second Model:

Dependent Variable: Monthly wage rate of construction workers who have received STP training.

Null Hypothesis (H_0): The current wage (2023) is less than the inflation adjusted wage

The regression models used in the analysis are as follows:

Model – 1:

$$Y = \beta_0 + \beta_1 Time + \beta_2 Trainee + \beta_3 STP\ time + \beta_4 Age + \beta_5\ Sex + \beta_6\ Religion + \beta_7 ST + \beta_8 SC + \beta_9 OBC + \beta_{10} Primary + \beta_{11} Middle + \beta_{12} High\ school + \beta_{13} HS + \beta_{14} Graduation\ \&\ above$$

Model – 2:

$$Y = \beta_0 + \beta_1 Time + \beta_2 Age + \beta_3\ Sex + \beta_4\ Religion + \beta_5 ST + \beta_6 SC + \beta_7 OBC + \beta_8 Primary + \beta_9 Middle + \beta_{10} High\ school + \beta_{11} HS + \beta_{12}\ Graduation\ \&\ above$$

Where,

Y is the dependent variable, β_0 is the intercept term and through are the coefficients for each independent variable where *n denotes 1, 2, 3,……*

Independent Variables

Time:

First Model: A dummy variable where:1 = Year 2023; 0 = Year 2019

Second Model: A dummy variable where:1 = Inflation-adjusted monthly wage rate in 2023; 0 = Current monthly wage received by workers in 2023.

STP (Skill Training Program):A dummy variable where:1 = Trainee workers; 0 = Non-trainee workers

STP Time (Interaction Term):A dummy variable representing the interaction of STP and Time, where:1 = Wage of trainee workers in 2023; 0 = Wage of all workers (trainee + non-trainee) in 2019

Age: Measured in years | Sex: Male = 1, Female = 0 | Religion: Hindu = 1, Muslim = 0

Social Group: Dummies for ST, SC, and OBC, with General (reference category) = 0

Education attainment: Dummies for Primary, Middle, High school, Higher Secondary, and Graduation and above, with literate but no formal education (reference category) =0

The second model is specially constructed for trainees only, hence, the variables "STP" and "STP time" are excluded from the model.

Adjustment of Wage Rate Using Cumulative Inflation Factor

The study utilizes the cumulative inflation factor to adjust the wage rate of construction workers over the study period. The cumulative inflation factor accounts for the compounding effect of annual inflation rates, ensuring an accurate adjustment of wage values over time. This approach is critical because inflation does not impact prices independently each year; rather, it builds on the price levels of previous years. By incorporating the cumulative effect, the method reflects the actual changes in purchasing power and cost of living more precisely. For instance, when calculating inflation-adjusted wages, the annual inflation rates are converted into factors and multiplied sequentially to obtain a cumulative value. This ensures that the adjusted wage accounts for the compounded nature of inflation, providing a more realistic representation of workers' economic conditions over time.

The study considers the Consumer Price Index (CPI) for the working-class population under the base year 2016, specifically for Assam. This is due to the fact that the workers under study belong to Assam, and their workplace is also within the state. Therefore, the CPI of Assam is more relevant for this analysis compared to the All-India CPI. The data for CPI was gathered from the *Assam Statistical Handbook* for the respective years. However, the CPI data for the year 2020 is not available due to disruptions caused by the COVID-19 pandemic. To address this gap, the CPI value for 2020 was estimated using the method of linear interpolation, based on the available CPI values for 2019 and 2021. The calculated CPI values, along with the corresponding inflation rates, are presented in the Table 1.

Table 1: CPI and Inflation Rate of Working-class Population

Year	CPI (base 2016)	Inflation rate
2019	112.10	6.52
2020	119.75	6.82
2021	127.40	6.39
2022	138.90	9.03
2023	144	4.10

Source: Authors' calculation using Statistical Handbook of Assam

Sample Profile

Table 2 illustrates the distribution of sample beneficiaries across districts, categorizing them into trainee, non-trainee, and overall groups. Dibrugarh emerges as a focal point, contributing significantly with 17.6% of trainees and non-trainees each. Districts like Jorhat, Chirang, Sivasagar, Udalguri, and Bongaigaon have a lower representation of sample beneficiaries which is lower than 5.0%.

Table 2: District-wise Distribution of Sample Trainees and Non-trainees (In %)

District	Trainee	Non-trainee	Overall
Baksa	8.0	8.0	8.0
Barpeta	10.1	10.1	10.1
Bongaigaon	2.5	2.5	2.5
Chirang	1.0	1.0	1.0
Darrang	11.6	11.6	11.6
Dhemaji	5.5	5.5	5.5
Dibrugarh	17.6	17.6	17.6
Jorhat	1.0	1.0	1.0
Kamrup	15.6	15.6	15.6
Nalbari	12.6	12.6	12.6
Sivasagar	2.5	2.5	2.5
Tinsukia	9.1	9.1	9.1
Udalguri	3.0	3.0	3.0
Total	**100**	**100**	**100 (n=398)**

Source: Primary Survey, 2023

Table 3 presents the demographic and socio-economic characteristics of construction workers, showing the mean or percentage distribution across various variables. The findings show that the workers' average age is 40 years (*Table 2*), indicating a relatively mature workforce. It is found that the construction workers include people from various castes and religions but is primarily gender specific with majority male workforce.

Table 3: Descriptive Statistics of the Sample (n=398)

Variables	Mean/Percentage	Std. Dev.	Min	Max
Time				
Year 2019	50	NA	0	1
Year 2023	50	NA	0	1
STP				
Trainee	50	NA	0	1
Non-trainee	50	NA	0	1
STP time				
Trained + non-trained workers in 2019	75	NA	0	1
Trained workers in 2023	25	NA	0	1
Age	40	9.78	16	62
Sex				
Male	99.8	NA	0	1
Female	0.3	NA	0	1
Social group				
ST	14.6	NA	0	1
SC	15.6	NA	0	1
OBC	35.2	NA	0	1
General	34.7	NA	0	1
Religion				
Hindu	93.0	NA	0	1
Muslim	7.0	NA	0	1
Education				
No formal education	7.8	NA	0	1
Primary	10.6	NA	0	1
Middle	36.9	NA	0	1
High school	24.9	NA	0	1
Higher secondary	16.1	NA	0	1
Graduation and above	3.8	NA	0	1

Source: Primary Survey, 2023

However, the significantly low representation of women (0.3%) is a worrying trend with regard to gender balance. When looking at the educational attainment of construction workers, it can be seen that many of the workers only have basic or secondary education (96.2%), the low share of higher education attainment among the construction workers

(3.8%) and vocational training is an indication of the need to re skill the workforce to be relevant in the current and future construction industry.

Results and Analysis

Comparison of Average Wages of the Trainee Workers Before and After STP

Table 4 presents a gender-wise breakdown of the average daily wage of the trainees engaged in various occupations before and after the Skills Training Program (STP). Before STP, the average daily wage for all trainees was Rs 341, with males earning Rs 343 and females earning Rs 100. After STP, there was a notable increase in average daily wages, reaching Rs 487 for all trainees, Rs 488 for males, and Rs 150 for females respectively. Across specific occupations like Carpenter, Electrician, Mason, Painter, and Plumber, similar patterns of improvement are observed.

Table 4: Gender-wise Composition of Average Daily Wage of the Workers from their Primary Occupation before as well as after STP (Those Who are Currently Engaged in the Trained Occupations)

Name of Occupation	Average daily wage (in Rs.)					
	Before STP			After STP		
	All	Male	Female	All	Male	Female
Carpenter	321	327	100	454	462	150
Electrician	350	350	-	505	505	-
Mason	342	342	-	470	470	-
Painter	359	359	-	521	521	-
Plumber	333	333	-	567	567	-
Total	341	343	100	487	488	150

Source: Primary survey, 2023

However, market forces and economic factors such as inflation can play a role in determining wages. While the STP may contribute to improved skills and productivity, external factors in the broader economic environment can also influence the overall compensation levels. Therefore, to find whether this increase in wages is due to STP or due to external factors, DiD method is employed which is discussed in the subsequent sections.

Impact of STP on Workers' Wages using DiD Method

Table 5 demonstrates that both non-trainee and trainee workers observed improvements in their average wages after the introduction of STP. Non-trainee workers experienced an average wage increase of Rs. 132, while trainee workers had a larger increase of Rs. 145. Consequently, the Difference-in-Differences (DiD) estimates of Rs. 13 indicate that, after the implementation of the STP, trainees, on average, earned Rs. 13 more than their non-trainee counterparts. This shows a favourable impact of the Skill Training Program on trainees' wages compared to what would have transpired in the absence of the program.

Table 5: DiD Estimates of Workers for Combining all Occupations

Group	Average wage		
	Pre-STP	Post-STP	Difference (Post-Pre STP)
Non-trainee (NT)	341	473	132
Trainee (T)	342	487	145
Difference (T - NT)	1	14	13
Counterfactual trend	341	474	-

Source: Authors' calculation using primary survey data, 2023

However, the impact of STP varies across occupational levels, and the following section will delve into the specific variation in STP's effects across different occupational categories.

Impact of STP on each Occupation

The Difference-in-Differences (DiD) analysis across five occupations as shown in Table 6 provides nuanced insights into the impact of STP on wage outcomes. For carpenters, the initial wage disparity of Rs. -17 between trainees and non-trainees narrowed to Rs. -9 post-STP, yielding a DiD estimate of Rs. 9, demonstrating a modest but positive impact of the program on carpentry trainees' earnings.

Among electricians, the DiD analysis revealed an Rs. 5 increase in wages for trainees, indicating a favorable yet modest effect of the STP on this occupation. In contrast, masonry workers experienced no discernible wage benefits from the program, with DiD estimates remaining at Rs. 0. Painters, however, witnessed a more substantial impact; while non-trainee painters saw an average wage increase of Rs. 137, trainee painters experienced a larger rise of Rs. 162, resulting in a DiD estimate of Rs. 25, highlighting the program's efficacy in significantly boosting their earning potential. Plumbers benefitted the most, with their initial wage gap of Rs. -17 widening to Rs. 42 post-STP, and the counterfactual trend suggesting that trainees would have earned Rs. 508 without the training. The resulting DiD estimate of Rs. 58 shows a substantial positive impact of the STP on plumbers' wages. Collectively, these findings emphasize the varying degrees of STP effectiveness across different professions, with notable successes in enhancing wages for painters and plumbers.

Table 6: DiD Estimates of Workers for Each Occupation

Group	Average wage (Rs.) Carpenter		
	Pre-STP	Post-STP	Difference (Post-Pre STP)
Non-trainee (NT)	339	463	124
Trainee (T)	321	454	133
Difference (T - NT)	-17	-9	9
Counterfactual trend	321	445	

Group	Average wage (Rs.) Electrician		
	Pre-STP	Post-STP	Difference (Post-Pre STP)
Non-trainee (NT)	365	515	150
Trainee (T)	350	505	155
Difference (T - NT)	-15	-10	5
Counterfactual trend	350	500	
Group	**Average wage (Rs.) Mason**		
	Pre-STP	**Post-STP**	**Difference (Post-Pre STP)**
Non-trainee (NT)	332	460	128
Trainee (T)	342	470	128
Difference (T - NT)	11	10	0
Counterfactual trend	342	471	
Group	**Average wage (Rs.) Painter**		
	Pre-STP	**Post-STP**	**Difference (Post-Pre STP)**
Non-trainee (NT)	357	493	137
Trainee (T)	359	521	162
Difference (T - NT)	2	28	25
Counterfactual trend	359	495	
Group	**Average wage (Rs.) Plumber**		
	Pre-STP	**Post-STP**	**Difference (Post-Pre STP)**
Non-trainee (NT)	350	525	175
Trainee (T)	333	567	233
Difference (T - NT)	-17	42	58
Counterfactual trend	333	508	

Source: Authors' calculation using primary survey data, 2023

Result from the Second Approach

In order to examine multicollinearity Variance inflation factor (VIF) is calculated. The VIF results show that there is no multicollinearity in the model (annexure 1).The results of the regression are shown in Table 7.

Table 7: Imact of STP on Wage Rate– Outputs from Linear Regression

	Model 1		Model 2	
Variables	**Coef.**	**Std. Err.**	**Coef.**	**Std. Err.**
Time (Year 2019®in first model) (Current wage® in second model)				

Year 2023 in first model; Inflation adjusted wage in second model	2903.62***	265.51	-1348.20***	357.08
STP (Non-trainee®)				
Trainee	-596.50**	250.11	NA	
STP time (Trained + non-trained workers in 2019®)				
Trained workers in 2023	956.25**	415.23	NA	
Age	15.48	11.45	7.21	22.91
Sex (Female®)				
Male	5951.95***	1054.75	6486.08***	536.43
Religion (Muslim®)				
Hindu	-1632.91***	439.87	-2939.12**	1148.08
Social Group (General®)				
ST	487.21	375.03	1488.15**	601.82
SC	489.03	322.84	447.46	552.98
OBC	558.74**	246.47	823.85**	423.29
Education (Below Middle®)				
Primary	804.37**	401.05	212.44	730.91
Middle	1247.19***	331.75	1281.31**	701.37
High school	1162.35***	356.37	964.47	645.27
HS	1061.87***	388.98	1084.22	707.19
Graduation and above	1715.23**	808.90	827.27	937.01
_cons	971.16	1254.01	5208.51***	1782.27
	Number of observations	787	Number of observations	389
	F(14, 772)	23.51***	F(12, 376)	24.53***
	R-squared	0.28	R-squared	0.14

Source: Authors' calculation using primary survey data, 2023

Interpretation of Results

The first model explores the determinants of monthly wages for construction workers, revealing significant insights into the role of training, demographic factors, and occupational differences. The coefficient for Time (2903.62, significant at 1%) indicates that controlling for other variables, wages increased by an average of Rs. 2,903.62 from 2019 to 2022. However, the negative coefficient for Trainee (-598.45, significant at 5%) suggests that workers who received STP training earn Rs. 598.45 less on average than those without training in the initial period, possibly due to differences in job roles or experience levels. Interestingly, the interaction variable STP Time (957.83, significant at 5%) shows that STP-trained workers experienced a wage increase of Rs. 957.83 in

2022 compared to other workers, indicating a delayed benefit of training. These result leads to accept the alternative hypothsis for the first model.

Among demographic factors, Male workers earn Rs. 5,985.69 more than females (significant at 1%), highlighting a gender wage gap. Hindu workers earn Rs. 1,732.17 less than Muslims (significant at 1%), suggesting potential socio-cultural wage differences. Social group coefficients for ST, SC, and OBC are positive but only OBC (601.42, significant at 5%) shows statistical significance, indicating higher wages relative to the general category.

The second regression analysis focuses on trainee construction workers in 2023, examining the determinants of their current and inflation-adjusted wages. The inclusion of the Time variable allows an assessment of whether current wages align with inflation-adjusted wages. The significant negative coefficient for Time (-1348.20, significant at 1%) indicates that the current wage is on average Rs. 1348.20 greater than inflation-adjusted wages, suggesting that the wages of trainee workers have kept pace with inflation, reflecting a real increase in their purchasing power. Based on this result alternative hypothesis is accepted for the second model.

Among demographic factors, Male workers earn Rs. 6486.08 more than females (significant at 1%), reinforcing the presence of a gender wage gap. Hindu workers earn Rs. 2,939.12 less than Muslims (significant at 5%), pointing to a socio-cultural disparity in wages. Among social groups, ST workers earn Rs. 1488.15 more (significant at 5%), while OBC workers earn Rs. 823.85 more (significant at 5%), compared to the general category, suggesting that certain groups may benefit from higher wages relative to the baseline group.

Discussion

The analysis of wage dynamics among construction workers using both the Difference-in-Difference (DiD) approach and regression models provides a comprehensive understanding of the impact of Skill Training Programs (STP). The DiD approach reveals a general positive effect of STP on wages, with trainees experiencing an average post-training wage hike of Rs. 13, surpassing the gains of non-trainees. However, the impact varies across occupations. For instance, painters and plumbers observed the largest post-STP wage increases of Rs. 58 and Rs. 26, respectively, highlighting the program's effectiveness in these fields. Carpenters and electricians also benefitted, with wage hikes of Rs. 9 and Rs. 5, respectively, while masonry workers showed no discernible change, indicating that certain occupations may require targeted interventions to enhance the effectiveness of training. These findings highlight the varied impacts of skill development initiatives across different occupations.

The regression analysis adds rigor to the findings by examining wage increases through two distinct models. The first model confirms that STP participation significantly raises wages compared to non-trainees, aligning with the DiD results. The second model provides deeper insights by distinguishing between current and inflation-adjusted wages. It reveals that the current wage is greater than inflation adjusted wage of trainees as indicated by the negative and significant coefficient of the inflation-adjusted wage variable. This improvement in current wages demonstrates that STP not only enhances earnings but also strengthens purchasing power, benefiting workers amidst inflationary pressures. A notable proportion of the wage increase can be attributed to productivity gains facilitated by training, as also highlighted by Dearden et al. (2006). The remaining increment, driven by inflationary pressures. Collectively, these insights highlight the dynamic role of STPs in boosting wages and empowering construction workers in the informal sector.

However, the analysis also reveals wage disparities across genders, with female workers earning less than their male counterparts, a trend consistent with findings by Shrestha et al. (2022) in the informal sector. This disparity may stem from differences in work experience, which were not accounted for in this study. Furthermore, educational attainment is found to have a significant influence on wage rates, though its effect may not be direct. Instead, education enhances workers' productivity, as suggested by Kampelmann et al. (2018), enabling them to utilize their skills more effectively and systematically. These findings highlight the factors influencing wage dynamics in the informal sector and show the need for holistic strategies to address wage inequalities and maximize the benefits of training programs.

Conclusion

This study investigates the impact of the Skill Training Program (STP) on the wages of construction workers in India using two distinct analytical approaches: Difference-in-Difference (DiD) and regression analysis. The findings consistently highlight the positive role of STP in enhancing workers' earnings and purchasing power, with variations across occupations and demographic groups.

The DiD analysis demonstrates that, on average, trainees experience a higher post-STP wage increase compared to non-trainees, with the magnitude of impact differing by occupation. Painters and plumbers showed the largest wage gains, while masonry workers exhibited no significant wage changes, indicating the need for occupation-specific interventions.The regression models provide further insights into wage dynamics. The first model establishes that participation in STP significantly boosts monthly wages for trainees. The second model reveals that current wages have increased beyond inflation-adjusted wages, signifying an improvement in the real purchasing power of trainee workers. These results underline the dual benefits of STP in not only raising wages but also shielding workers against inflationary pressures.

Appendix

The VIF results are shown in annexure 1.

Variables	VIF	1/VIF
Time	1.98	0.51
Trainee	2.3	0.43
STP time	3.03	0.33
Age	1.29	0.77
Male	1.02	0.98
Hindu	1.27	0.78
ST	1.37	0.72
SC	1.34	0.74
OBC	1.46	0.68
Primary	2.20	0.45
Middle	3.99	0.25
High school	3.62	0.27
HS	3.03	0.32
Graduation and above	1.59	0.63
Mean VIF	2.10	

Source: Authos's calculation

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