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# Identifying Wage Disparities in Construction Labor Market by Job Types, Experiences, and Locations across the United States

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This study focuses on the critical examination of wage disparities within the expansive landscape of the United States' construction labor market. While wage differentials are not surprising considering different conditions of job requirements, comprehending and delineating these disparities on a national scale presents considerable challenges. To address this issue, this study employs web scraping techniques to collect data from construction job openings across the country. This study then applies natural language processing techniques to extract information related to wages, job types, work experience requirements, and geographical locations of the job postings. This approach involves web scraping, text mining, ANOVA analyses, and spatial visualization techniques to detect and represent wage disparities within the construction labor market. This research not only contributes to creating a structured repository of wage disparity data but also provides a visual understanding of the intricate landscape of wage differentials, revealing interactions between various key variables. This research will serve as a valuable resource not only to researchers but also to policymakers and employers, contributing to a deeper understanding of wage disparities within the construction labor domain.

**Key Words:** Construction Workforce, Web Scraping, Text Mining, ANOVA

## Introduction

The International Labor Organization (ILO) emphasizes the pivotal role of wages as a fundamental component of working conditions and a central focus of collective bargaining (International Labor Organization, 2023b). This collaborative process between employees and employers, involving the negotiation and definition of employment terms, plays a vital role in job preservation, business continuity, and securing income of workers. Recognizing wage disparities stemming from job types, experience levels, and geographical locations within the industry is crucial (International Labor Organization, 2023a). These variations are shaped by the nuances of roles, required skill sets, responsibilities, and geographic factors affecting wage structures. A comprehensive understanding of these gaps is indispensable for businesses, aiding informed decisions on employee compensation,

talent attraction and retention, and fostering equity within the workforce. Additionally, understanding these wage variations plays a vital role in addressing disparities and ensuring fair compensation for workers across different contexts.

Naturally, wages fluctuate based on different factors such as job types, experience levels, and geographical locations within the industry (International Labor Organization, 2022). These fluctuations are a result of job complexity, required skill sets, task severity, and specific role demands. Moreover, regional variations in living costs significantly contribute to wage disparities among different areas (Dumond et al., 1999). Despite the reasons behind these variations, accurately quantifying wage differentials remains a complex and dynamic task, influenced by various factors. Thoroughly acknowledging and analyzing these disparities is imperative for upholding fairness and equity in the workforce and addressing wage disparities.

The construction industry presents a unique challenge in identifying wage differentials, primarily due to its distinct characteristics, such as widely dispersed job locations. Given the dynamic nature of the construction industry and the multitude of variables introduced by projects spanning urban and rural areas, understanding wage differentials within this industry is crucial. This understanding is valuable not only for job seekers but also for policymakers, employers, and workforce development agencies. Several studies have focused on identifying wage differentials for specific groups within the construction industry, such as skilled laborers, apprentices, and minority workers. For instance, one study aimed to detect Hispanic and non-Hispanic wage disparities in the construction industry (Goodrum, 2004). Another study investigated employment and wage distribution by gender (Shrestha et al., 2020). Researchers also strive to introduce spatial analysis to comprehend wage gaps (Manesh et al., 2020). However, existing research has significant limitations due to its small number of data points.

This research aims to identify wage differentials in the U.S. construction job market by analyzing job postings across the country. According to an OECD report (Carnevale et al., 2014; Co-operation and Development, 2021), online job postings encompass over 60% of all job listings and provide a rich source of textual data, including job titles, descriptions, requirements, locations, wages, and more. Accordingly, this research is conducted under the assumption that detecting disparities in suggested wages on job postings can provide insights into wage disparities in the job market. Natural language processing and text mining techniques are employed to extract pertinent information from each context, followed by ANOVA tests and data visualization to derive meaningful insights. The utilization of ANOVA tests is crucial in this analysis, as it is a powerful method for examining variations (Scheffe, 1999). The findings will significantly contribute to our understanding of wage variations in the construction labor market, shedding light on the factors influencing wage disparities in an industry characterized by diverse and dispersed job locations (Goswami and Lall, 2015).

## **Methodology**

This study initiated the data collection process by scraping online job postings (Oh et al., 2023). Text mining methods are then employed to extract details of the job postings, including wages, locations, job types, and minimum required years of experience. This process resulted in the identification of 108,917 job postings as the final dataset, encompassing complete information for all variables with no missing values. Additional data from external sources such as Bureau of Labor Statistics (BLS) for job types information (U.S. Bureau of Labor Statistics, 2022), United States of Agriculture (USDA) for rural-urban levels (U.S. Department of Agriculture, 2020), the Federal Reserve Bank for the Cost

of Living Database (CLD) (Federal Reserve Bank of Atlanta, 2023), and U.S. Census Application Programming Interface (API) for American Community Survey (ACS) (U.S. Bureau of Labor Statistics, 2023) were integrated. Each dataset was assigned to the main dataset based on locational information. The datasets are mainly at the county level, and locations of the job postings are converted to coordinates using Google API to facilitate joining at the county level. The research delivers two main outcomes: 1) application of analysis of variance (ANOVA) and Multiple Linear Regression (MLR) to analyze wages concerning required minimum experience, job types, cost of living, and rural-urban classifications, and 2) data visualization for wage differentials based on the ANOVA and MLR results.

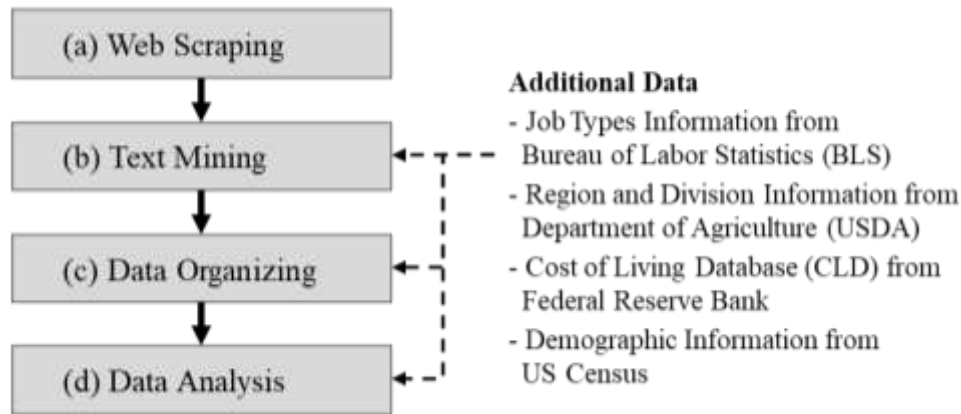


Figure 1. Research Framework

This study builds upon earlier research conducted (Oh et al., 2022). To extract details of job information from job postings, this research employs Named Entity Recognition (NER) techniques. For example, based on dollar characters, programming code detects wages and terms regarding units such as hour, day, drill, week, month, and year. Most job postings present wage information as a range, such as "from \$15" or "from \$15 to \$20". In these cases, this research considers a small number of detected dollars, taking into account their associated "required minimum experience", which is one of main variables in this study. Regarding job locations, most job postings include cities or towns, which are converted to latitude and longitude coordinates using the Google API. These coordinates are further mapped to counties through spatial join techniques, allowing additional data assignment at the county level, such as cost of living and rural-urban classifications.

This research then extensively analyzes the dataset using ANOVA and MLR analyses. Additionally, the study introduces the average ratio of actual wage to predicted wage within each county, offering insights into wage and predicted model. The result is visualized graphically, providing a comprehensive understanding of geographic wage variations.

## Results

This study first illustrates the descriptive statistics of the dataset in Table 1.

Table 1

*Descriptive Statistics for Raw Data*

Variables	Key Features of 108,917 Job Postings
Wage (\$/hour)	Mean: 20.0506, Standard Deviation:8.6473
Living Cost	Mean: 32.6624, Standard Deviation: 4.3380
Job Type (Counts)	Number of data points by job type: Construction equipment operators (19,005), Electricians (16,881), Carpenter (16,344), Plumbers, pipefitters, and steamfitters (12,098), Welders, cutters, solderers, and brazers (10,169), Air conditioning, and refrigeration mechanics and installers (8,571), Painters, construction and maintenance (7,774), Roofers (5,461), Construction and building inspectors (2,876), Flooring installers and tile and marble setters (2,426), Solar photovoltaic installers (1,988), Mason(1,844), Ironworkers (1,297), Drywall installers, ceiling tile installers, and tapers (1,013), Heating, Glaziers (959), Hazardous materials removal workers (107), Elevator and escalator installers and repairers (59), Boilermaker (45),
Experience (Counts)	Number of data points by required minimum experience: 1year (43,951), 2year (21,037), 3year (18,127), 4year (4,875), 5year (15,767), 5+year (5,160)
Rural-urban (Counts)	Number of data points by rural-urban code: (higher indicates more rural areas) Metro: 1 (58,230), 2 (26,615), 3 (10,938) Non-metro: 4 (4,548), 5 (1,911), 6 (3,925), 7 (1,830), 8 (443), 9 (477)

The final model from ANOVA tests examines the relationship between hourly minimum wage and several factors: job types, required minimum experience, cost of living, and urban levels. The formula used in ANOVA is “Wage ~ Job Type · Experience · Living Cost · Rural-ruban”. It indicates an investigation into the impact of these factors individually and in combination, accounting for their combined effects and interactions. This approach aims to understand how changes in job types, required experience, cost of living, and urban settings collectively influence the hourly minimum wage. The summary of the test is shown in Table 2.

Table 2

*ANOVA Test Result*

Variables	Sum Sq.	F-value	P-value
Job Type	803,542	735.447	< 2e-16
Experience	209,043	3,252.574	< 2e-16
Living Cost	55,164	858.323	< 2e-16
Rural-urban	18,756	291.831	< 2e-16
Job Type:Experience	32,811	30.031	< 2e-16
Job Type:Living Cost	8,963	8.203	< 2e-16
Job Type:Rural-urban	14,294	13.083	< 2e-16
Experience:Living Cost	1,858	28.907	7.61e-08
Experience:Rural-urban	675	10.507	6.07e-05
Living Cost:Rural-urban	1,034	10.507	0.00119

The ANOVA analysis uncovers significant interactions affecting hourly minimum wages, specifically those between job types and various factors like required minimum experience, cost of living, and urban levels. These interactions reveal the diverse impacts that these variables have within industries. Notably, the interaction “Job Type:Experience” interaction demonstrates influencing wages more profoundly. The interaction between job types and urban levels, though slightly lower in impact compared to job type and required minimum experience, also significantly contributes to explaining wage variability. Although other interactions such as “job types:cost of living” hold statistical significance, their impact appears comparatively less when considering sum of squares and F-value. These findings highlight the multifaceted relationships between different variables, collectively shaping hourly minimum wages and contributing to our understanding of wage disparities.

The outcomes of the ANOVA analysis prompt a deeper exploration into specific variable interactions with notable impacts on hourly minimum wage. In particular, the interactions of “Job Type:Experience”, “Job Type:Rural-urban”, and “Experience:Living Cost” have higher Sum Sq. and F-value compared to other interactions. Trendlines are illustrated in Figure 2 to 4, explaining the nuanced relationships between factors that influence hourly wage trends. These visual representations explain the relationships between job types and required minimum experience ranging from 1 to 5 years, offering insights into the varied impact of experience on hourly wages across professions.

Figure 2 provides a visualization of the relationship between hourly wage and the required minimum experience, segmented by job types. Each trendline illustrates the wage dynamics as experience levels vary. For instance, job type such as "Electrician" exhibit a steady wage increase with experience, while others such as "Operator" depict rapid initial salary growth between 1 and 2 years of experience. This variance in wage changes reveals the impact of experience on hourly minimum wage across the different professions.

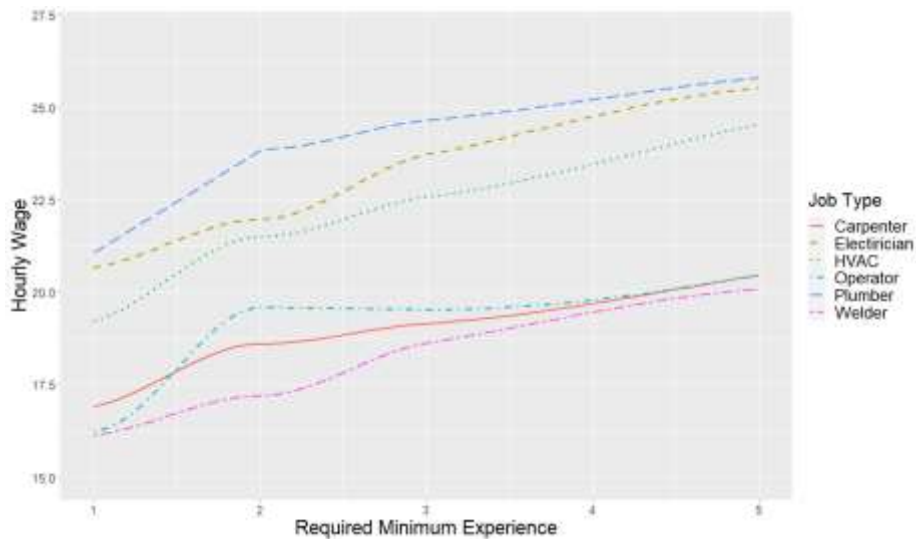


Figure 2. Hourly Wage Trends by Job Type and Required Experience

Figure 3 explores hourly wage trends categorized by job type and rural-urban levels. It reveals higher wages for most job types in urban areas, aligning with expected urbanized wage trends. However,

wage disparities appear across different rural-urban levels. Notably, rural-urban level nine, defined as "Completely rural or less than 2,500 urban population, not adjacent to a metro area", demonstrate a distinct surge in wages in some job types, indicating potential challenges in sourcing workers due to the remote nature of these locations, potentially driving higher wages. Additionally, significant shifts in specific job types exhibit a notable decrease from level 1 to level 2, suggesting potential surges in job demand or remote locations from workers locations, such as their living places. These variations show the necessity for a more comprehensive exploration into wage adjustments within different job types across rural and urban landscapes.

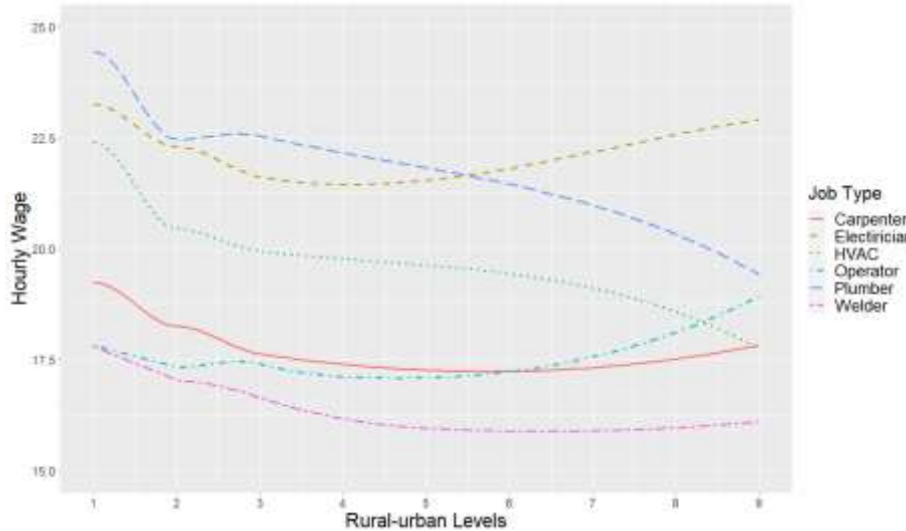


Figure 3. Hourly Wage Trends by Job Type and Rural-urban Level

Figure 4 visually explains the trendlines depicting hourly wage trends categorized by required experience and cost of living. Trends across different cost-of-living show similar patterns in all required minimum experience. Particularly noteworthy is the tendency for areas with very lower costs of living to offer higher hourly wages, often linked to remote or less urbanized regions attracting workers with relatively higher wages. Furthermore, the exponential nature of wage increments in higher cost of living across all trendlines suggests benefits of working at expensive areas. Understanding these trends becomes crucial for workers and employers in making informed decisions related to job locations, potential financial gains, and living costs.

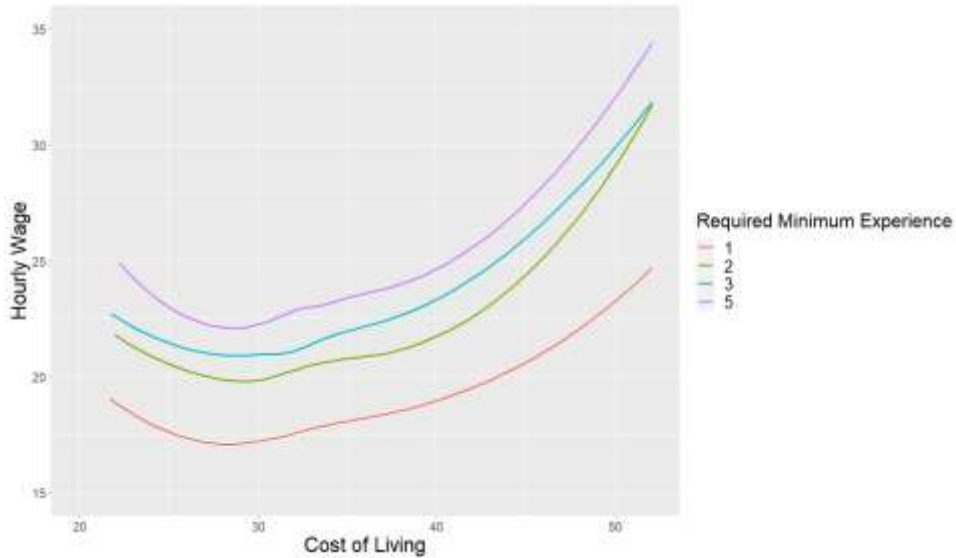


Figure 4. Hourly Wage Trends by Required Experience and Cost of Living

To further clarify interactions, this research employed a 70/30 data split and a multiple linear regression model to develop findings independent of random data partitions. The aim was to identify the model with the highest R-squared value. Figure 5 utilizes geospatial visualization to merge demographic data and information at county-level geographical boundaries. It displays the average of residual ratios, representing actual wages over predicted wages by regression results, with data points in each block across the counties. When the block does not include more than five data points, they are excluded in this study. This visualization offers insights into the geographic distribution of hourly minimum wages and associated attributes, providing a comprehensive summary at the county level. This aids in identifying regions where workers potentially earn notably higher wages compared to similar counterparts in other areas.



Figure 5. Residual Ratio by Counties

## Conclusions

The findings from ANOVA analyses and comprehensive visualizations provide valuable insights into the complex dynamics of wage disparities within the construction labor market across the United States. The interactions between job types, required experience, cost of living, and rural-urban levels illuminate the multifaceted influences shaping hourly minimum wages. Notably, rural-urban disparities and the impact of experience on wages demonstrate the need for a deeper understanding of wage adjustments within various job types across diverse landscapes.

Moreover, geospatial visualization offers an overview of hourly wage disparities, revealing regions where workers potentially earn higher-than-expected wages based on job type, experience, living costs, and urban settings. These variations highlight the nature of wage adjustments within different job types across diverse rural and urban landscapes, suggesting potential correlations between variables. Understanding these nuances is crucial for both workers and employers, influencing decisions regarding job location, financial gains, and living costs.

In exploring the wage disparities within the construction labor market, our findings not only offer an overview of the current state but also lay the groundwork for future inquiries. Beyond considerations of job types, required experience, and geographical variations, the dynamic nature of the construction industry requires further investigation. For example, collaborating with industrial contractors and engaging HR compensation professionals could provide practical insights for both industry applications and academic research.

In addition, as industries adapt to evolving trends, including technological advancements and the emergence of remote work, future research could explore how these factors interplay with wage dynamics. Understanding the evolving landscape is vital for anticipating industry shifts, making informed decisions, and fostering a workforce that thrives in a rapidly changing environment.

This research will aim to serve as a valuable resource to researchers but also to policymakers and employers, in making more informed decisions about compensation strategies, talent acquisition, and geographical employment patterns. Understanding these intricate interactions is vital for fostering equity within the workforce and facilitating more strategic decision-making within the construction labor market.

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