MODELING U.S. WAGE GROWTH DETERMINANTS USING MULTIPLE LINEAR REGRESSION IN EVIEWS

1. Overview

Client:

A workforce analytics consultancy serving enterprise HR departments and public labor agencies in the United States

Objective:

To quantify the effects of individual and sectoral characteristics on wage growth using multiple linear regression in EViews, enabling data-driven workforce planning and compensation benchmarking.

2. Background

In light of changing labor market dynamics, clients needed to understand what drives wage differentials across demographics and industries. Prior internal studies relied on Excel-based summaries and simple correlations. A robust regression framework using EViews was introduced to measure the marginal contribution of each factor to wage growth.

3. Data Summary

Dataset:

American Community Survey (ACS) 5-Year Estimates (2017–2021 sample)

Sample Size:

12,000 individual-level observations (cleaned and stratified)

Variables Used:

Variable	Type	Description
Hourly_Wage (log)	Continuous	Log of hourly wage (USD)
Education_Level	Categorical	Dummy-coded: High School, Bachelor's, Graduate
Years_of_Experience	Continuous	Total work experience in years
Gender	Dummy	1 = Male, 0 = Female

Union_Membership	Dummy	1 = Yes, 0 = No
Industry	Categorical	Dummies for Manufacturing, Services, Tech, etc.
Region	Dummy	Dummies for Northeast, Midwest, South, West

4. Methodology

Software Used:

EViews 13

Model Type:

Multiple Linear Regression (OLS)

EViews Workflow:

1. **Data Import and Cleaning:**
   - Imported .csv data
   - Dummy variables generated using genr command for Education, Industry, and Region
2. **Model Estimation:**
   - *Quick > Estimate Equation*
   - Dependent Variable: log(Hourly_Wage)
   - Regressors: Education dummies, Experience, Gender, Union, Industry, Region
3. **Diagnostics:**
   - VIFs for multicollinearity
   - Breusch–Pagan test for heteroskedasticity
   - RESET test for model specification
   - Cook's Distance for influence diagnostics
4. **Robust Standard Errors:**
   - Re-estimated model with White heteroskedasticity-consistent errors

5. Key Results

Predictor	Coefficient (β)	Significance (p-value)	Interpretation
Bachelor's Degree	+0.158	0.000	+17.1% wage increase vs. high school (exp(0.158)–1)
Graduate Degree	+0.272	0.000	+31.3% higher wage vs. high school
Years of Experience	+0.014	0.001	1.4% increase in wage per year of experience
Gender (Male)	+0.094	0.002	9.8% higher wages than female
Union Membership	+0.087	0.005	Union workers earn 9.1% more on average
Tech Industry	+0.208	0.000	Tech workers earn 23.1% more than manufacturing baseline

Adjusted R^2: 0.63 **F-Statistic:** Significant at 1% **VIF values:** < 2.1 for all predictors (no multicollinearity detected)

6. Visual Outputs (Created in EViews)

- Histogram of residuals to verify normality
- Actual vs. fitted wage chart
- Influence plots with Cook's D overlay
- Bar chart of standardized coefficients for interpretability

7. Deliverables

- EViews .wf1 file with model, graphs, and regression table
- 13-page report including:
  - Regression theory and application
  - Interpretation of outputs
  - Diagnostic results and robustness checks

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    - Strategic implications for HR policy
- Supplemented with:
    - Excel summary table for HR dashboard use
    - Executive memo summarizing top wage drivers

8. Outcomes & Client Impact

- Used to redesign job grading and salary bands across departments
- Informed diversity pay equity review (via gender and union coefficients)
- Presented in strategic planning session for workforce reskilling investments

9. Strategic Value Delivered

- Delivered **empirical transparency** to wage-setting processes
- Helped quantify the **return to education and experience** across industries
- Provided statistically defensible insights for **HR strategy and compliance**

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