Group 8: Occupational Abilities and Wage Outcomes

Course: Programming for Business Analytics

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1 Introduction

The U.S. labor market has undergone a long-run shift away from work centered on physical effort toward occupations that emphasize cognitive and abstract abilities. This transformation reflects not only changes in sectoral composition but also a deeper reallocation of tasks within occupations driven by automation and digital technologies. As production processes evolve, the economic value of different types of human abilities has shifted accordingly, with important implications for wage outcomes.

Recent advances in artificial intelligence have further reinforced these patterns. Digital technologies increasingly automate routine tasks (Autor et al., 2003; Acemoglu & Autor, 2011), including some forms of routine cognitive work such as data processing and information retrieval, while complementing non-routine analytical and interpersonal activities. These developments have intensified concerns about job displacement (Frey & Osborne, 2017) and wage inequality, alongside growing evidence that high-skill occupations benefit disproportionately from technological change (Autor & Dorn, 2013). Together, these trends suggest that the ability composition of occupations plays a central role in shaping occupational wage outcomes in the contemporary labor market.

This study examines the relationship between occupational abilities and wage outcomes in the United States. Drawing on detailed ability measures from O*NET and occupational wage data from the Bureau of Labor Statistics, the analysis addresses the following question:

Which types of occupational abilities are most strongly associated with wage outcomes across occupations?

2 Literature Review

A large body of research examines how technological change alters labor demand and wage outcomes by shifting the relative value of occupational abilities. A foundational framework is skill-biased technological change (SBTC), which posits that new technologies increase the productivity of skilled workers relative to less-skilled workers, thereby raising demand and wages for the former (Katz & Murphy, 1992; Autor et al., 2003). Building on this framework, Autor, Levy, and Murnane (2003) argue that computerization substitutes for labor in routine, codifiable tasks while complementing labor in non-routine analytical and interactive tasks. As a result, occupations intensive in abstract cognitive abilities tend to be associated with more favorable wage outcomes, while routine manual and clerical occupations face weaker labor market rewards (Acemoglu & Autor, 2011).

Subsequent research adopts a task-based perspective that classifies jobs by the nature of the tasks they involve rather than by education level alone. This literature documents job polarization, characterized by the coexistence of high-wage, high-skill occupations and low-wage service jobs alongside the contraction of middle-wage, routine-intensive occupations (Autor & Dorn, 2013). Wage outcomes are closely aligned with this structure: cognitive-intensive professional and technical occupations generally command higher pay, whereas many routine middle-skill jobs exhibit weaker wage outcomes. Studies focusing on specific abilities further show that not all cognitive skills are equally rewarded. Deming (2017) finds that social and communication abilities are strongly associated with favorable wage outcomes, while Bacolod and Blum (2010) emphasize the role of cognitive and people-oriented abilities in explaining wage differences across occupations.

Evidence using occupational task and ability data reinforces these patterns. Analyses based on O*NET data show that occupations requiring higher levels of reasoning and communication abilities consistently exhibit more favorable wage outcomes than occupations emphasizing physical or psychomotor abilities. Recent advances in automation and artificial intelligence have further sharpened these distinctions. While automation tends to replace labor in routine tasks, AI technologies can also augment cognitively intensive work, leading to divergent wage outcomes across occupations depending on task content (Acemoglu & Restrepo, 2019; Marguerit, 2025). Taken together, the literature suggests that the ability composition of occupations plays a central role in shaping wage outcomes, motivating the present analysis of how broad groups of occupational abilities are associated with wage outcomes across occupations.

3 Data Description and Construction

3.1 Data Sources

3.1.1 O*NET Abilities Database & Job Family

The primary source for occupational skill requirements is the Occupational Information Network (O*NET) database, specifically the “Abilities” file (Version 29.1, published November 2024). O*NET is the primary source of occupational information in the United States, providing standardized descriptors for 52 distinct human abilities across nearly 1,000 occupations defined by the Standard Occupational Classification (SOC) system.

For each occupation and ability, O*NET reports a “Level” score (ranging from 0 to 7), indicating the degree of complexity the ability requires to perform the job. For example, the ability “Inductive Reasoning” might have a low level requirement for a “Dishwasher” but a high level requirement for a “Pathologist.” We utilized the “Level” scale (Scale ID = “LV”) for our analysis, as it captures the intensity of the requirement rather than just its importance.

To facilitate sectoral analysis, we utilized the O*NET “All_Job_Families.xlsx” file, which maps detailed SOC codes to broader functional categories (e.g., “Management,” “Production,” “Computer and Mathematical”). This allows for the visualization of ability distributions across different sectors of the economy and helps to contextualize the regression results within specific industries.

3.1.2 BLS Occupational Employment and Wage Statistics (OEWS)

Wage data were obtained from the Bureau of Labor Statistics (BLS) Occupational Employment and Wage Statistics (OEWS) program. We collected annual files for the years 2014 through 2024 to capture a decade of wage dynamics. The OEWS program produces employment and wage estimates for over 800 occupations. The key variable of interest is A_MEAN (Annual Mean Wage), which represents the estimated total annual wages of an occupation divided by its estimated employment.

We log-transformed this variable (log_wage) to approximate a normal distribution and facilitate the interpretation of coefficients as percentage changes.

3.2 Variable Construction and Processing

The raw data required significant processing to be suitable for econometric analysis. This process was conducted using the R programming language, leveraging packages such as dplyr, tidyr, and purrr for data manipulation.

3.2.1 Classification of Abilities

Following the O*NET content model, the 52 detailed ability elements were classified into four broad dimensions based on their element_id prefixes:

- **Cognitive** (1.A.1): Includes 21 abilities related to thinking, reasoning, memory, and expression (e.g., Deductive Reasoning, Oral Expression, Memorization).
- **Psychomotor** (1.A.2): Includes 10 abilities related to fine motor control and manipulation (e.g., Finger Dexterity, Reaction Time, Arm-Hand Steadiness).
- **Physical** (1.A.3): Includes 9 abilities related to strength and endurance (e.g., Static Strength, Trunk Strength, Stamina).
- **Sensory** (1.A.4): Includes 12 abilities related to visual and auditory perception (e.g., Near Vision, Hearing Sensitivity, Night Vision).

3.2.2 Aggregation and Standardization

The raw data provided ability scores at the element level (e.g., "Inductive Reasoning"). To create manageable indices for regression analysis, we performed the following transformations:

- Aggregation: We calculated the mean "Level" score for all elements within each of the four broad groups (Cognitive, Physical, Psychomotor, Sensory) for each occupation. This reduced the dimensionality of the data from 52 variables to 4 key indices.
- Standardization: To ensure comparability across different scales and to facilitate the interpretation of regression coefficients, we standardized these aggregate scores into z-scores, $z = (x - \mu)/\sigma$. A score of $+1.0$ indicates that an occupation requires that ability at a level one standard deviation above the national average. This transformation is crucial because the raw "Level" scales may not be directly comparable across different ability types.

3.2.3 Wage Variable Construction

The dependent variable is the natural logarithm of the annual mean wage (`log_wage`). To focus on structural, long-run relationships rather than short-term business cycle fluctuations, we aggregated the wage data by calculating the mean log_wage for each occupation over the 11-year sample period (2014–2024). This resulted in a cross-sectional dataset where each observation represents a unique occupation (N = 763) with a stable measure of its long-run wage potential.

While this aggregation pools nominal wages from varying price levels (2014–2024), we rely on the assumption that inflationary pressures impact the occupational wage structure uniformly. Consequently, while the absolute dollar values have changed due to inflation, the relative hierarchy of wages between occupations—which is the focus of this cross-sectional analysis—remains stable. This averaging approach serves to smooth out idiosyncratic year-specific shocks (e.g., the COVID-19 pandemic) to isolate the permanent component of occupational earnings. Specifically, we filtered the BLS data to include only detailed occupations (removing broad category aggregates like "00-0000") and matched them to the O*NET data via SOC codes.

3.2.4 Final Sample Characteristics

The final dataset consists of 763 unique occupations with complete information on both ability requirements and wages. Exclusions were primarily limited to military-specific occupations, newly emerging occupations that do not have complete wage observations over the 2014–2024 period, and other niche roles for which O*NET ability information was incomplete or not directly comparable to civilian occupations.

Job families in this study are defined according to the O*NET job family classification, which groups detailed SOC occupations into broader functional categories. The excluded occupations represent narrowly defined or recently introduced roles that account for a small share of SOC codes and are not central to the long-run civilian occupational structure captured by the O*NET job family framework. Their removal therefore does not materially affect the distribution of occupations across ONET job families or the descriptive patterns of ability composition shown in Figure 2. As a result, the final sample remains broadly representative of the U.S. occupational structure for the purposes of analyzing long-run associations between occupational abilities and wages.

4 Methodology

4.1 Analysis Strategy Identification

Our empirical strategy examines the association between occupational ability requirements and wages using a cross-sectional approach. Because O*NET ability measures change slowly and are not updated frequently enough to form a meaningful annual panel, we aggregate the data to long-run averages and estimate cross-sectional regressions at the occupation level.

The analysis is explicitly associational rather than causal. We do not rely on an exogenous shock or policy intervention, as occupational ability requirements are relatively stable job characteristics. Accordingly, the estimated coefficients should be interpreted as capturing the long-run market valuation of different bundles of abilities across occupations in the U.S. labor market over the 2014–2024 period.

Because wages are averaged over time and expressed in nominal terms, the estimates reflect long-run nominal differences in wages across occupations. To the extent that higher-cognitive occupations may have experienced faster real wage outcomes, the estimated associations may represent a conservative lower bound of the cognitive wage premium.

Therefore, the original dataset is structured as a panel, with repeated observations of wages and ability requirements for each occupation over 11 years. To align the data with the identification strategy, wages and ability measures are averaged across the entire sample period for each occupation. This transformation yields a cross-sectional dataset in which each observation represents an occupation's long-run average characteristics rather than year-specific fluctuations. As a result, the estimated coefficients capture average associations over an 11-year horizon rather than short-run or year-specific effects.

4.2 Analysis Steps

4.2.1 Exploratory Correlation Analysis

Before estimating the regression model, we examine pairwise correlations among the key variables to assess potential overlap in occupational ability requirements. This exploratory analysis provides preliminary insight into the relationships among the explanatory variables but does not constitute a formal test for multicollinearity.

4.2.2 Regression Model

To test our hypothesis regarding the impact of different categories of abilities, we estimate the following Ordinary Least Squares (OLS) regression model:

$$\overline{\log(wage)}_j = \beta_0 + \beta_1 \overline{Cognitive}_j + \beta_2 \overline{Physical}_j + \beta_3 \overline{Psychomotor}_j + \beta_4 \overline{Sensory}_j + \varepsilon_j.$$

where j indexes occupations. All ability measures are standardized, and the dependent variable is the 11-year average of log wages for each occupation. Based on the literature review, we hypothesize that cognitive ability has the strongest impact on wage outcomes.

4.2.3 Multicollinearity Diagnostics

Because occupational ability requirements may overlap across dimensions, multicollinearity is a potential concern in regressions that include multiple ability measures simultaneously. To assess the extent of this issue, we compute Variance Inflation Factors (VIFs) for all explanatory variables.

4.2.4 Robustness Test

Given the cross-sectional nature of the data, another concern is heteroskedasticity, as wage variability may differ across occupations and ability profiles.

To assess this issue, we first examine residual-versus-fitted plots to visually assess potential heteroskedasticity. Then, to statistically test this pattern, we conduct the Breusch–Pagan test, which provides statistical evidence on whether heteroskedasticity is present.

5 Results

5.1 Initial Analysis

Before interpreting the regression estimates, descriptive analysis provides background on broad patterns in wages and ability composition across occupations.

5.1.1 Wage Trends

Average log wages exhibit a steady and approximately linear upward trend over the 2014–2024 period. The mean log wage increases from around 10.75 in 2014 to approximately 11.15 in 2024. This pattern reflects sustained nominal wage outcomes over the sample period and indicates limited short-term volatility. The smoothness of the trend suggests that averaging wages over the 11-year horizon provides a stable representation of long-run occupational wage differences.

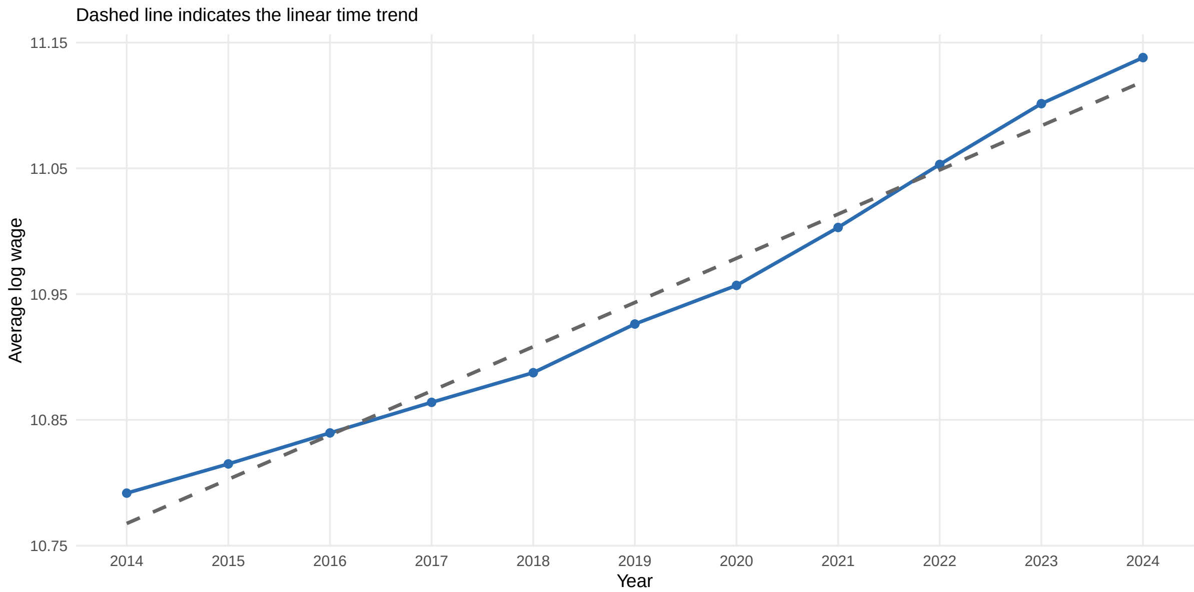

Figure 1: Average log wage over time

5.1.2 Ability by Job Family

Figure 2 presents heatmaps of average standardized ability scores across O*NET job families. The results reveal clear structural differences in ability composition across occupations.

- **Cognitive Intensity**: Cognitive ability requirements are highest in Management, Computer and Mathematical, Architecture and Engineering, and Legal occupations. These job fami-

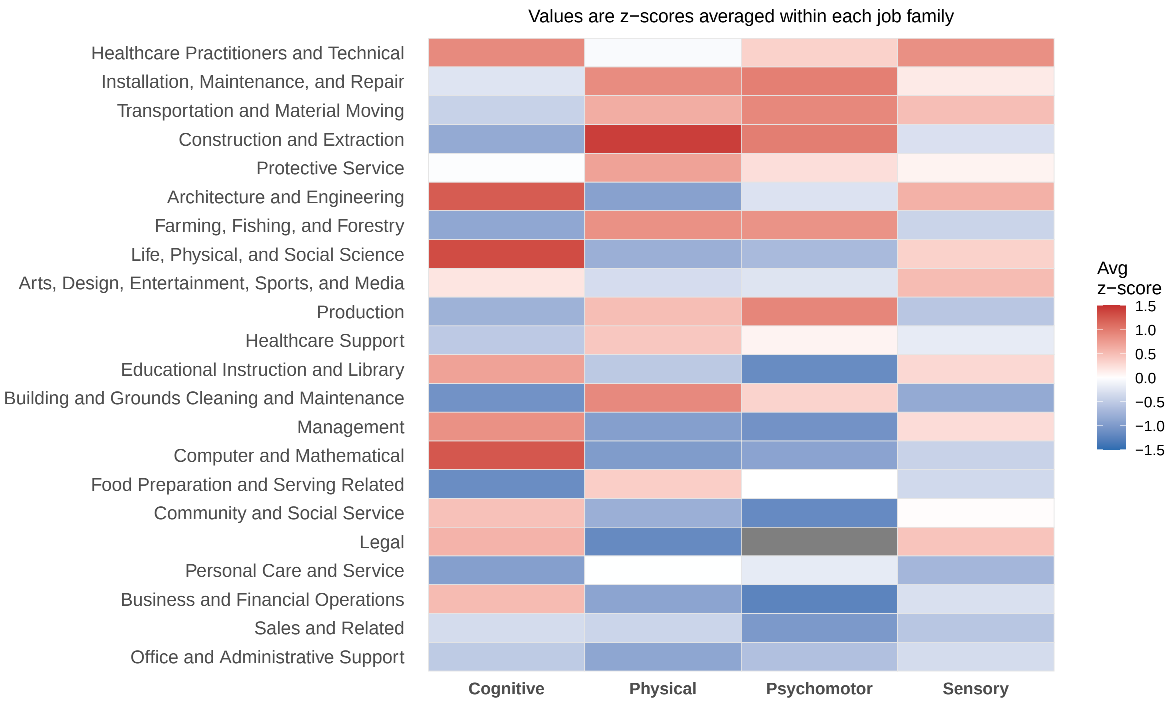

Figure 2: Average standardized ability composition by job family

lies exhibit average cognitive z-scores exceeding +1.0, indicating substantially above-average cognitive demands.

- **Physical and Psychomotor Intensity**: Physical and psychomotor abilities are most prominent in Construction and Extraction, Installation, Maintenance, and Repair, and Production occupations. These job families display high positive z-scores in physical and psychomotor dimensions alongside below-average cognitive intensity.

- **Sensory Intensity**: Sensory ability requirements show less variation across job families. Slightly elevated sensory intensity is observed in Healthcare Practitioners and Technical and Arts, Design, Entertainment, Sports, and Media occupations, reflecting greater demands for visual and auditory precision.

Overall, the descriptive patterns confirm substantial heterogeneity in the composition of ability requirements across job families, motivating the multivariate regression analysis that follows.

5.2 Model testing

5.2.1 Correlation

Table 1: Correlation matrix of average ability

	avg_cognitive	avg_physical	avg_psychomotor	avg_sensory
avg_cognitive	1.000	-0.484	-0.380	0.559
avg_physical	-0.484	1.000	0.702	-0.088
avg_psychomotor	-0.380	0.702	1.000	0.080
avg_sensory	0.559	-0.088	0.080	1.000

The correlation matrix shows systematic relationships among the ability dimensions. Cognitive ability is moderately negatively correlated with physical ($r = -0.48$) and psychomotor abilities ($r = -0.38$), while it is positively correlated with sensory ability ($r = 0.56$). Physical and psychomotor abilities are strongly positively correlated ($r = 0.70$), whereas sensory ability exhibits weak correlations with physical and psychomotor dimensions. Overall, the correlations suggest overlap among some ability measures but do not indicate severe collinearity.

5.2.2 Regression Model with 4 Groups of Ability

We estimate the following occupation-level model using 11-year averages:

$$\log(\text{wage})_j = \beta_0 + \beta_1\,\text{Cognitive}_j + \beta_2\,\text{Physical}_j + \beta_3\,\text{Psychomotor}_j + \beta_4\,\text{Sensory}_j + \varepsilon_j$$

where j indexes occupations (SOC). Each ability variable is standardized (z-score), and the outcome is the 11-year average of log wage for each occupation.

Table 2: Ability composition and average occupational wages

	(1)
Cognitive ability	0.393***
	(0.015)
Physical ability	−0.012
	(0.016)
Psychomotor ability	0.023
	(0.016)
Sensory ability	−0.010
	(0.014)
Constant	10.956***
	(0.010)
Num.Obs.	746
R2	0.646
R2 Adj.	0.644
AIC	256.4
BIC	284.1

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Substituting the estimated coefficients, the fitted regression equation can be written as:

$$\log(\text{wage})_j = 10.956 + 0.393\,\text{Cognitive}_j - 0.012\,\text{Physical}_j + 0.023\,\text{Psychomotor}_j - 0.010\,\text{Sensory}_j + \varepsilon_j$$

According to Table 2, at the occupational level, cognitive ability is the only ability group that is significantly associated with wage differences across jobs.

Cognitive ability: The estimated coefficient is 0.393 ($p < 0.001$), indicating that a one standard deviation increase in an occupation's average cognitive requirement is associated with 0.393 log points higher average wages, holding other ability groups constant. Because the dependent variable is expressed in logarithmic form, this coefficient can be interpreted in proportional terms. Specifically, a one standard deviation increase in cognitive ability is associated with approximately a 48 percent increase in average wages ($exp(0.393) - 1 \approx 0.48$). Because all ability measures are standardized as z-scores, so a one-unit increase corresponds to a one standard deviation difference relative to the occupational average rather than a one-point increase on the raw O*NET Level scale. This standardization facilitates comparability across ability dimensions and supports interpretation in terms of economically meaningful differences in occupational skill intensity.

The magnitude of this effect is consistent with the descriptive patterns shown in Figure 2 O*NET job families with substantially above-average cognitive intensity, such as Management, Computer and Mathematical, Legal, and Architecture and Engineering, tend to be associated with higher wage levels than job families with below-average cognitive intensity, such as Food Preparation and Serving Related or Building and Grounds Cleaning and Maintenance. The regression results therefore formalize these descriptive differences by quantifying the average wage gap associated with cognitive skill intensity across occupations.

Physical, psychomotor, and sensory abilities are not statistically significant ($p > 0.10$). This suggests that, once cognitive requirements are taken into account, these other ability dimensions do not explain additional variation in wages across occupations in this averaged job-level data.

Overall, the model exhibits a strong fit ($R^2 \approx 0.65$), indicating that the four broad ability groups jointly account for a substantial share of cross-occupational wage variation.

5.2.3 Multicollinearity Check

To assess potential multicollinearity among the explanatory variables, we examined variance inflation factors (VIFs) using the `performance` package.

Table 3: Variance inflation factors (VIFs) abilities variables

Term	VIF	Tolerance
avg_cognitive	2.13	0.47
avg_physical	2.21	0.45
avg_psychomotor	2.17	0.46
avg_sensory	1.70	0.59

The results indicate that all VIF values range from 1.70 to 2.21, which are well below the commonly accepted threshold of 5, and even below the more conservative threshold of 3. In addition, tolerance values range from 0.45 to 0.59, further suggesting that multicollinearity is not a concern in the present model. Overall, these diagnostics indicate low correlation among the four ability dimensions, allowing the estimated coefficients to be interpreted reliably.

5.2.4 Robustness Check

To assess the robustness of the baseline regression results, we examine the presence of heteroskedasticity in the error terms and evaluate whether the main findings are sensitive to this issue.

5.2.4.1 Heteroskedasticity Diagnostics

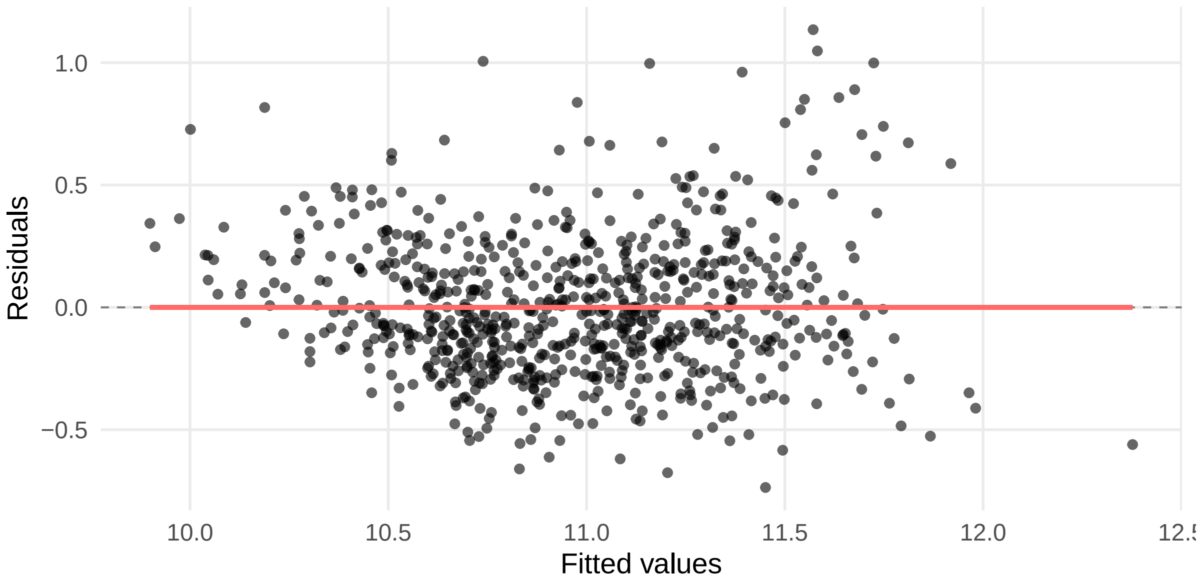

Figure 3: Residuals versus fitted values for the baseline OLS Model 1

Plots residuals against fitted values from the baseline OLS model. The dispersion of residuals appears to vary across the range of fitted values, suggesting non-constant error variance.

Then we test statisticallty for heteroskedasticity using the studentized Breusch–Pagan test.

Table 4: Breusch–Pagan test for heteroskedasticity

	Statistic	BP	df	p.value
BP	Breusch–Pagan	29.112	4	<0.001

Table 4 reports the results of the studentized Breusch–Pagan test.The null hypothesis of homoskedastic errors is strongly rejected ($BP = 29.11, df = 4, p < 0.001$), indicating the presence of heteroskedasticity in the residuals. This result is consistent with the residuals-versus-fitted values plot, which suggests non-constant variance across the range of fitted values.

5.2.4.2 Robust Standard Errors

To account for heteroskedasticity, all standard errors are therefore computed using heteroskedasticity-robust estimators (HC1). This adjustment corrects statistical inference while leaving the coefficient estimates unchanged.

Table 5: Baseline regression with heteroskedasticity-robust standard errors (HC1)

	(1)
Cognitive ability	0.393***
	(0.017)
Physical ability	−0.012
	(0.017)
Psychomotor ability	0.023
	(0.019)
Sensory ability	−0.010
	(0.013)
Constant	10.956***
	(0.010)
Num.Obs.	746
R2	0.646
R2 Adj.	0.644
AIC	256.4
BIC	284.1

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Robust (HC1) standard errors are reported in parentheses.

The regression results from table Table 5 obtained using heteroskedasticity-robust standard errors remain qualitatively unchanged. Cognitive ability continues to exhibit a strong and statistically significant positive association with average log wages, while physical, psychomotor, and sensory abilities remain statistically insignificant. This indicates that the main findings are robust to heteroskedasticity.

5.3 Deeper Insight from Cognitive Ability

While the aggregate results show that cognitive ability plays a central role in explaining cross-occupational wage differences, treating cognitive ability as a single composite measure may conceal important heterogeneity within this broad category. Cognitive skills in O*NET span a range of distinct functions, from higher-order reasoning and communication to more routine cognitive tasks such as memory and attentiveness. To capture this variation, the analysis further decomposes cognitive ability into seven sub-dimensions defined by O*NET, allowing for a more precise identification of which specific cognitive skills drive the overall wage–ability relationship.

Cognitive sub-dimensions (O*NET classification):

- **Reasoning** (Idea Generation and Reasoning Abilities): Abilities related to analyzing information, generating ideas, and solving novel or complex problems. These abilities reflect higher-order cognitive processes central to problem solving and decision making.
- **Verbal Abilities**: Abilities related to the acquisition, comprehension, and application of verbal information, including reading, writing, and oral communication, which are essential for communication-intensive tasks.
- **Quantitative Abilities**: Abilities that influence the solution of problems involving mathematical relationships, numerical reasoning, and quantitative analysis.
- **Spatial Abilities**: Abilities related to the manipulation and organization of spatial information, such as visualizing objects, patterns, and spatial relationships.
- **Memory**: Abilities related to the recall of available information, including remembering words, numbers, pictures, and procedures. These abilities are often associated with routine information processing rather than complex problem solving.
- **Attentiveness**: Abilities related to sustaining attention and concentration during task performance, particularly in tasks requiring monitoring and accuracy.
- **Perceptual Abilities**: Abilities related to the acquisition and organization of visual information, including recognizing patterns, differences, and visual details.

5.3.1 Correlation

Table 6: Correlation matrix of cognitive ability sub-dimensions

	verbal	reasoning	quantitative	memory	perceptual	spatial	attentiveness
verbal	1.000	0.898	0.701	0.753	0.446	0.151	0.200
reasoning	0.898	1.000	0.761	0.757	0.632	0.373	0.347
quantitative	0.701	0.761	1.000	0.636	0.565	0.322	0.212
memory	0.753	0.757	0.636	1.000	0.585	0.230	0.400
perceptual	0.446	0.632	0.565	0.585	1.000	0.512	0.669
spatial	0.151	0.373	0.322	0.230	0.512	1.000	0.382
attentiveness	0.200	0.347	0.212	0.400	0.669	0.382	1.000

The correlation matrix indicates substantial overlap among several cognitive sub-dimensions. Verbal and reasoning abilities are highly correlated ($r \approx 0.90$), and both are strongly correlated with quantitative ability ($r \approx 0.70$–0.76), suggesting that these dimensions capture closely related cognitive skills. Memory also shows moderate to strong correlations with verbal, reasoning, and quantitative abilities ($r \approx 0.64$–0.76).

In contrast, spatial ability exhibits relatively weak correlations with verbal and memory abilities but moderate correlations with perceptual ability ($r \approx 0.51$). Attentiveness is moderately correlated with perceptual ability ($r \approx 0.67$) and weakly to moderately correlated with other cognitive dimensions. Overall, the correlations suggest overlap among several cognitive sub-dimensions, motivating post-estimation multicollinearity diagnostics in the regression analysis.

5.3.2 Regression Model with Sub-groups of Cognitive Ability

The regression model decomposing cognitive ability into sub-dimensions is specified as follows:

$$\begin{aligned}\log(\text{wage})_j = \beta_0 &+ \beta_1\,\text{Reasoning}_j + \beta_2\,\text{Quantitative}_j + \beta_3\,\text{Verbal}_j \\ &+ \beta_4\,\text{Memory}_j + \beta_5\,\text{Attentiveness}_j + \beta_6\,\text{Perceptual}_j + \beta_7\,\text{Spatial}_j + \varepsilon_j\end{aligned}$$

Table 7: Cognitive ability sub-dimensions and average occupational wages

	(1)
Reasoning	0.220***
	(0.032)
Quantitative	0.016
	(0.017)
Verbal	0.172***
	(0.029)
Memory	−0.059***
	(0.018)
Attentiveness	0.011
	(0.015)
Perceptual	0.032+
	(0.019)
Spatial	0.047***
	(0.013)
Constant	10.965***
	(0.010)
Num.Obs.	744
R2	0.662
R2 Adj.	0.659
AIC	226.2
BIC	267.7

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

Substituting the estimated coefficients, the fitted regression equation can be written as:

$$\begin{aligned}\log(\text{wage})_j = 10.965 &+ 0.220\,\text{Reasoning}_j + 0.016\,\text{Quantitative}_j + 0.172\,\text{Verbal}_j \\ &- 0.059\,\text{Memory}_j + 0.011\,\text{Attentiveness}_j + 0.032\,\text{Perceptual}_j + 0.047\,\text{Spatial}_j + \varepsilon_j\end{aligned}$$

The results indicate that cognitive sub-dimensions contribute differently to wage differences across occupations. As shown in Table 7, **Reasoning** ability exhibits a strong positive association with average log wages ($\beta = 0.220, p < 0.001$), followed by **Verbal** ability ($\beta = 0.172, p < 0.001$) and **Spatial** ability ($\beta = 0.047, p < 0.001$).

Because the dependent variable is expressed in logarithmic form, these coefficients can be interpreted as proportional wage differences. Specifically, a one standard deviation increase in reasoning ability is associated with approximately a 25 percent higher average wage ($exp(0.220) - 1 \approx 0.25$), while comparable increases in verbal and spatial abilities are associated with wage differences of roughly 19 percent and 5 percent, respectively.

In contrast, **Memory** is negatively associated with wages ($\beta = -0.059, p < 0.01$), while **Perceptual** ability is only marginally significant. **Quantitative** ability and **Attentiveness** do not exhibit statistically significant associations with wages once other cognitive sub-dimensions are taken into account. Interpreted in proportional terms, a one standard deviation increase in memory requirements is associated with an approximately 6 percent lower average wage ($exp(-0.059) - 1 \approx -0.06$).

These results should be interpreted in a conditional sense. In the multivariate model, each coefficient reflects the association between a specific cognitive sub-dimension and log wages while holding other cognitive abilities constant. As illustrated in Figure 2, job families with high overall cognitive intensity, including Management, Computer and Mathematical, Legal, and Architecture and Engineering, tend to be characterized by strong reasoning and communication demands and are associated with higher average wage levels.

By contrast, job families such as Office and Administrative Support, Food Preparation and Serving Related, and Building and Grounds Cleaning and Maintenance exhibit lower overall cognitive intensity and weaker wage outcomes, despite often involving routine memory and attentiveness demands. Once higher-order cognitive skills are accounted for in the regression model, memory-intensive requirements appear to be more characteristic of these lower-wage occupational groups. In short, the negative coefficient on memory suggests that the labor market rewards higher-order cognitive functions more strongly than routine memory-based task demands.

Overall, the model explains a substantial share of cross-occupational wage variation ($Adjusted\ R^2 \approx 0.66$), indicating that the wage premium associated with cognitive ability is primarily driven by reasoning, verbal, and spatial skills rather than by memory or attentiveness alone.

5.3.3 Multicollinearity Check

Table 8: Multicollinearity diagnostics for cognitive sub-dimensions (VIF)

Term	VIF	Tolerance
reasoning	9.526209	0.1049736
quantitative	2.675795	0.3737206
verbal	7.771951	0.1286678
memory	2.928025	0.3415271
attentiveness	2.020850	0.4948413
perceptual	3.327686	0.3005091
spatial	1.593451	0.6275688

VIF diagnostics suggest generally low to moderate multicollinearity. Reasoning and verbal abilities exhibit higher VIF values, reflecting their conceptual overlap, but multicollinearity does not appear severe enough to compromise coefficient interpretation.

5.3.4 Robustness Check

5.3.4.1 Heteroskedasticity Diagnostics

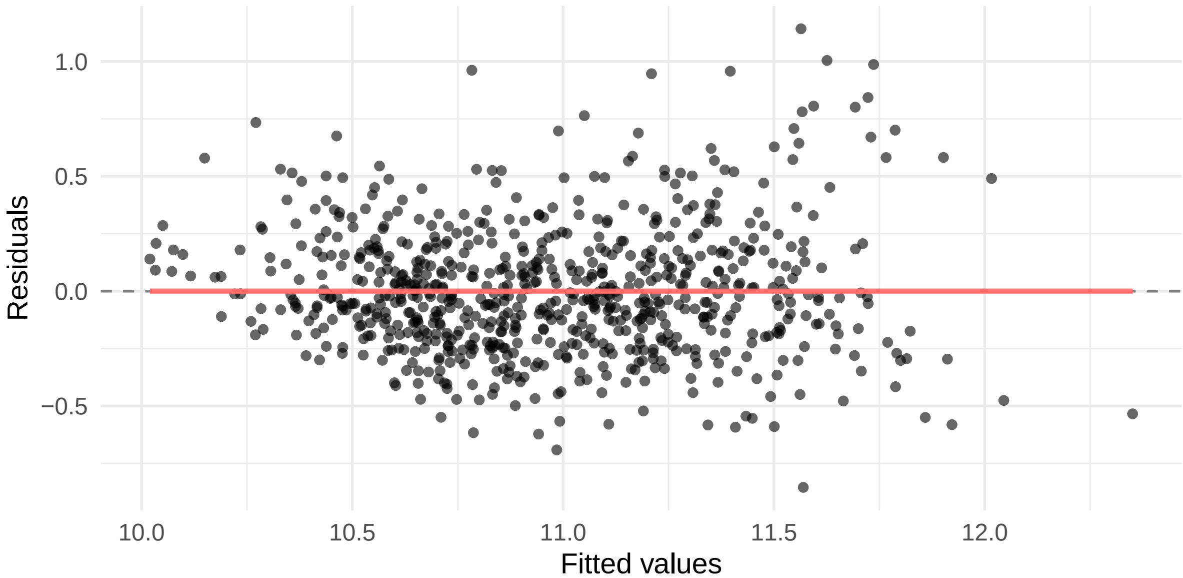

Figure 4: Residuals versus fitted values for the baseline OLS Model 2

The residuals-versus-fitted plot provides visual evidence that the dispersion of residuals appears to vary across the range of fitted values. This pattern suggests potential heteroskedasticity in the error terms.

Table 9: Breusch–Pagan test for heteroskedasticity (cognitive sub-dimensions model)

	Statistic	BP	df	p.value
BP	Breusch–Pagan	64.53	7	<0.001

Table 9 reports the results of the studentized Breusch–Pagan test for the cognitive sub-dimensions model. The null hypothesis of homoskedastic errors is rejected ($BP = 64.53, df = 7, p < 0.001$), indicating the presence of heteroskedasticity in the residuals. This result suggests that the variance of the error terms is not constant across observations.

5.3.4.2 Robust Standard Errors

Table 10: Cognitive sub-dimensions and wages with heteroskedasticity-robust standard errors

	(1)
Reasoning	0.220***
	(0.036)
Quantitative	0.016
	(0.018)
Verbal	0.172***
	(0.029)
Memory	−0.059**
	(0.018)
Attentiveness	0.011
	(0.015)
Perceptual	0.032
	(0.020)
Spatial	0.047***
	(0.013)
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AIC	226.2
BIC	267.7

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001
Robust (HC1) standard errors are reported in parentheses.

The results remain qualitatively unchanged when using robust standard errors. Reasoning, verbal, and spatial abilities continue to exhibit positive and statistically significant associations with average log wages, while memory remains negatively associated with wages. Attentiveness, quantitative, and perceptual abilities remain statistically insignificant. Overall, the main findings of the cognitive sub-dimensions model are robust to heteroskedasticity.

5.4 Conclusion of Two Models and Study Limitation

5.4.1 Conclusion of Two Models

Taken together, the two regression models yield consistent and complementary conclusions regarding the relationship between occupational abilities and wages. At the aggregate level, cognitive ability emerges as the only broad ability group that is robustly and positively associated with wage differences across occupations. Physical, psychomotor, and sensory abilities do not exhibit statistically significant associations once cognitive requirements are taken into account, suggesting that cross-occupational wage variation is primarily driven by cognitive skill demands.

When cognitive ability is decomposed into sub-dimensions, the results further clarify the sources of this wage premium. Higher-order cognitive skills, particularly reasoning, verbal, and spatial abilities, are strongly and positively associated with wages, indicating that occupations requiring problem-solving, communication, and spatial reasoning tend to command higher pay. In contrast, memory-intensive task requirements are negatively associated with wages once other cognitive sub-dimensions are held constant. This finding suggests that routine cognitive demands are less strongly rewarded in the labor market than higher-order cognitive functions, a pattern that is consistent with the descriptive differences in ability composition across O*NET job families.

5.4.2 Study Limitation

Several limitations of this study should be acknowledged.

First, the analysis is conducted at the occupational level using averaged wage and ability measures. As a result, the findings capture differences across occupations rather than variation among individual workers within occupations. This aggregation may mask substantial within-occupation heterogeneity in skills, job tasks, and wages.

Second, the empirical strategy relies on cross-sectional variation and does not identify causal effects. Ability requirements and wages are jointly determined in equilibrium, and unobserved factors—such as educational requirements, industry composition, unionization, or licensing—may influence both occupational wages and measured ability demands. Consequently, the estimated coefficients should be interpreted as associations rather than causal returns to specific abilities.

Finally, wages are averaged over the period 2014–2024. While this approach reduces sensitivity to short-term shocks, it also limits the ability to capture changes in the relative returns to different abilities over time, particularly in response to technological change.

6 Conclusion

This study examines how different types of occupational abilities are associated with wage differences across jobs using O*NET ability measures and long-run average wage data. The results show that cognitive ability plays a central role in explaining cross-occupational wage variation, while physical, psychomotor, and sensory abilities do not contribute additional explanatory power once cognitive requirements are considered.

Importantly, the findings demonstrate that not all cognitive skills are equally rewarded. Higher-order cognitive abilities related to reasoning, communication, and spatial processing are strongly associated with higher wages, whereas routine cognitive demands such as memory and attentiveness do not generate comparable wage premiums when other cognitive skills are taken into account. This distinction highlights the importance of moving beyond aggregate measures of cognitive ability to examine the specific skill components that drive labor market outcomes.

Overall, the results suggest that occupational wage structures primarily reward cognitive skills that support complex problem solving, abstraction, and effective communication. By distinguishing between different types of cognitive demands, this study provides a more nuanced understanding of how occupational skill requirements are reflected in wage differences across jobs.

7 Reference

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